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Implementing Intentional Robotics Principles using SSR2K Platform

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Abstract—**We demonstrate the operation of the SODAS approach (Self-organized Ontogenetic Development of Autonomous Systems) for on-line processing of sensory inputs and onboard dynamic behavior tasking using SRR2K (Sample Return Rover) platform at the Planetary Robotics indoor facility of JPL. SODAS employs a biologically inspired dynamic neural network architecture operating on the principle of chaotic neural dynamics manifesting intentionality in the style of brains. Intentional behavior includes the cyclic operation of prediction, testing by action, sensing, perceiving, and assimilating the learned features. The experiments illustrate robust obstacle avoidance combined with goal-oriented navigation by the SRR2K robot.**

I. INTRODUCTION

BIOLOGICALLY-inspired control architectures are widely used for guidance and navigation control of mobile robots. One research direction aims at modeling animal navigation without necessarily modeling brain regions; e.g., landmark-based navigation [1]-[3]; cognitive maps using associative networks [4]; hierarchy based on complexity analysis [5], [6]. Various biologically-inspired approaches demonstrated robust navigation capabilities in challenging real life scenarios, like subsumption methods [7], [8], BISMARC (Biologically Inspired System for Map-based Autonomous Rover Control) [9]-[11]; ethology inspired hierarchical organizations of behavior [12]; behavior-based control algorithm using fuzzy logic [13]; robot collaboration [14], [15].

Brain-like architectures and modeling brain activity related to spatial navigation and orientation is an increasingly popular area of intelligent control, including learning cognitive maps in the hippocampus [16], [17], the role of place cells in navigation [18]; visual mapping and the hippocampus [19]; learning in the cortico-hippocampal system [20], [21].

These brain models exhibit complex spatio-temporal dynamics due to the massive recurrent connections within and between the brain regions. Following Clark, such models are called third generation connectionist models [22]. Third generation connectionist models include DARWIN [23], [24], and the Distributed Adaptive Control (DAC) models [25], [26].

In this work we apply to SODAS architecture for robot navigation [20], [27]. Preliminary results have been published in [28]. SODAS is a novel connectionist architecture with massive recurrent connections between its nodes which exhibit complex spatio-temporal dynamical behavior. Therefore, SODAS can be classified as a member of third generation connectionist systems. SODAS is based on the hierarchy of K (Katchalsky) sets, which have been introduced by Freeman based on his decade-long studies into the structure and dynamics of the olfactory sensory system [29], [30]. K sets are essentially multi-layer neural networks with massive recurrent connections between excitatory and inhibitory neural populations arranged in layers. Although K sets have been originally introduced for modeling olfaction, there is ample of evidence indicating that K sets grasp the essential mechanisms of sensory processing in vertebrate brains across various sensory modalities [31], [32], [33], [34].

K sets consist of a hierarchy of components of increasing complexity, including the K0, KI, KII, KIII and the KIV system. K0 is the basic building block of the K sets. It models the input-output behavior of neurons with an asymmetric nonlinear sigmoid function. A KI set combines a population of either excitatory or inhibitory K0 sets. KII set is formed from KI sets by connecting both excitatory and inhibitory KI units. Note that a KI set has a simple convergent dynamics to a fixed point, while KII can exhibit limit cycle oscillations following initial transients.

The KIII model consists of several interconnected KII sets, and it models a given sensory system in brains, e.g., olfactory, visual, auditory, somatosensory modality. It has been shown that KIII can be used as an associative memory which encodes input data into nonconvergent spatio-

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temporal oscillations [31], [32]. The KIII nonconvergent/ chaotic memories have several advantages as compared to convergent recurrent networks: (1) they produce robust memories based on relatively few learning examples even in noisy environment; (2) the encoding capacity of a network with a given number of nodes is exponentially larger than their convergent counterparts; (3) they can recall the stored data very quickly, just as humans and animals can recognize a learnt pattern within a fraction of a second [33], [34].

KIV is the K set with the highest complexity and it models multisensory processing, decision making, and basic forms of intentional action. KIV consists of several KIII sets. KIV has KIII sets for the following modalities:

- Exteroception: e.g., vision, audition, tactile sensing;
- Interoception: including, hunger, fear, frustration;
- Orientation: location of the system in space and time.

The feasibility and competitiveness of K-based mobile robot control has been demonstrated on various simple platforms. KIII-based navigation has been implemented on a Khepera robot simulation environment [35]. The results compare very well with Vershure's results in the original Distributed Adaptive Control experiment [36], and with the object avoidance performance of Schmitt trigger [37]. Further successful demonstrations of the KIV-based control are given using a simulated 2D Martian environment [38], as well as using the Sony Aibo ERS 220 mobile robot platform [39].

The rest of this paper is organized as follows. In the next section we describe the SODAS intentional dynamical system based on a KIV set. We implement the developed system for the autonomous control of SRR2K (Sample Return Rover). Finally we describe results of learning and autonomous navigation using the integrated SODAS-SRR system at JPL planetary robotics indoor facility.

II. Principles of Intentional Autonomous Systems

A. Intentionality in Biological Systems

The key features of intentionality in humans and animals are summarized as follows:

Intelligent behavior is characterized by the flexible and creative pursuit of endogenously defined goals. Humans and animals are not passive receivers of perceptual information. They actively search for sensory input. To do so they must form hypotheses about expected future states, and express these as goals such as safety, fuel, or temperature control. They must formulate a plan of action, and they must inform their sensory and perceptual apparatus about the expected future input in a process called re-afference. They must manipulate their sense organs, take information in the form of samples from all of their sensory ports, then generalize, abstract, categorize, and combine into multisensory percepts (Gestalts). These new data serve to verify or negate the hypotheses and update the brain state, including information about the location of the animal or human in its environment. *The cyclic operation of prediction, testing by action, sensing, perceiving, and assimilation is called intentionality* [40].

The significance of the dynamical approach to intelligence is emphasized by our hypothesis that nonlinear dynamics is a key component of intentional behavior in biological systems [41], [42]. The proposed dynamical hypothesis on intentionality and intelligence goes beyond the basic notion of goal-oriented behavior, or sophisticated manipulations with symbolic representations to achieve given goals. Intentionality is endogenously rooted in the agent and it can not be implanted into it from outside by any external agency. Intentionality is manifested in and evolved through the dynamical change in the state of the agent upon its interaction with the environment. Implementation of intentional dynamics for robot control is described below.

B. Intentional Robot Control

KIV is the brain of an intentional robot that acts into its environment by exploration and learns from the sensory consequences of its actions. The architecture and nonlinear neurodynamics of the KIV brain are modeled on the vertebrate brain. By cumulative learning it creates an internal model of its environment, which it uses to guide its actions while avoiding hazards and reaching goals that the human controller defines.

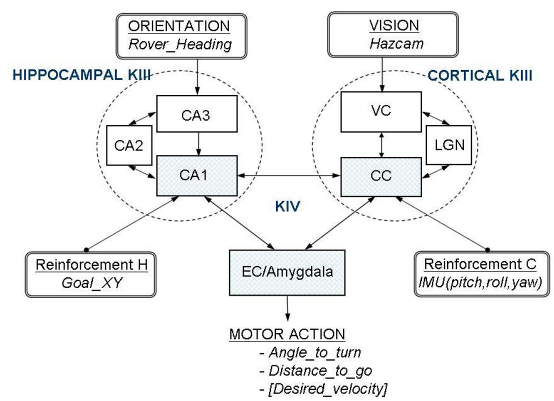

Figure 1. Schema of the simplified KIV model used in the SODAS control experiments. Notations of the KII units: CA1, CA2, and CA3 are hippocampal sections; VC and CC are visual cortex and cerebral cortex, respectively, LGN is lateral geniculate nucleus; EC – entorhinal cortex. Specification of orientation and vision sensory signals, and hippocampal and cortical reinforcement signals is given separately in SRR description. Shaded boxes indicate locations where learning (CA1 and CC) and recall (EC/Amygdala) take place.

The KIV-guided robot uses its experience to continuously solve problems in perception and navigation that are imposed by its environment as it pursues autonomously the goals selected by its trainer.

The complete KIV model consists of four major components, out of which three are KIII sets [27]. Namely, a KIII models the hippocampus, another one models the cortical region, and the third describes the midline forebrain. The fourth major component is the entorhinal cortex (EC) with amygdala, which is a KII set. EC integrates influences from all parts of the hemisphere, and it provides link to external parts of the limbic system for motor action. In the present work and simplified KIV is used, including a visual sensory KIII set, a hippocampal KIII set. For simplicity, we have a reinforcement signal representing the interoceptory unit, instead of a KIII midline forebrain KIII. Accordingly, EC integrates the effects of cortical and hippocampal KIII units. The applied KIV set is depicted in Fig. 1.

Learning takes place in the CA1 and CC units of the hippocampus and cortex, respectively. We have two types of learning: Hebbian correlation learning, and habituation. Hebbian learning is paired with reinforcement, reward or punishment; i.e., learning takes place only if the reinforcement signal is present. This is episodic, not continuous, long-term and irreversible. Habituation, on the other hand results in continuous degradation of the response of a cell in proportion of its activity, unless reinforced by long-term memory effects; see [31] and [32] for details.

III. SRR2K EXPERIMENTAL PLATFORM

A. Control Architecture and Finite State Machine

Experiments are conducted at the indoor facility of the Planetary Robotics Group, JPL. It includes an approximately 5x5m irregularly shaped test area covered by sand and rocks imitating natural exploration environments. The terrain layout is variable from smooth surface for easy advance to rough terrain with various hills and slopes posing more challenges to SRR2K traversing through it. The lighting conditions are adjustable at need.

SRR2K is a four-wheeled mobile robot with independently steered wheels and independently controlled shoulder joints; see Fig.2. Its mass is 7 kg, and the maximum power use during fast movement (30–50 cm/s) is around 35 W can only be sustained for about 6 h without recharging the batteries. In the small experimental environment in this study, no large distances are traveled, so the battery capacity is not an actual limitation for us. SRR computing includes a 266 MHz Pentium II processor in a PC/104+ stack that operates under the real-time OS VxWorks5.4.

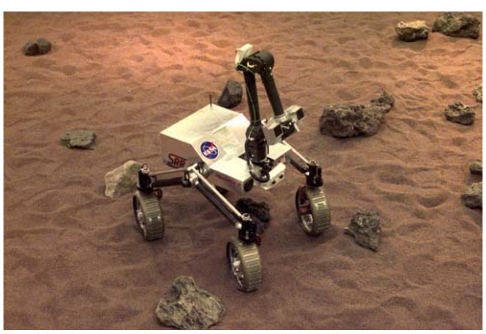

Figure 2. SRR2K situated in the environment.

The primary sensing modalities on SRR2K include: (1) a stereo camera pair of 5 cm separation, 15 cm of height and 130 degree field of view; (2) a goal camera mounted on a manipulator arm with 20 degree field of view; (3) internal DMU gyroscope registering along coordinates pitch, roll, and yaw; (4) Crossbow accelerometer in x, y, and z coordinates; (5) a Sun sensor for global positioning information [43].

To simplify measurement conditions and data acquisition, the top-mounted goal camera, the robot arm, and the global positioning sensor are not used in the present experiments. This work is based on measurements by the stereo camera and the DMU unit only. This approach simplifies the technical support and signal monitoring needs, but it also poses a more challenging task for efficient and reliable goal completion.

SODAS prototype has been developed in Matlab environment [44]. The SODAS package contains about 100 hierarchical module files written in Matlab R14. In the framework of the present limited project, we keep SODAS on the existing Matlab platform, which runs on a desktop PC. This PC communicates with the on-board SRR2K computer via telnet link. As most of the signal processing and feature extraction takes place on-board, we do not require broad-band communication. SODAS accesses the low-dimensional sensory data vectors from SRR2K and provides a control file cmd55 containing outputs of SODAS control concerning the states of the Finite State Machine running on SRR2K.

SODAS incorporates a short-term memory (STM) with a given depth, as well as associative long-term memory (LTM). The STM could be 3-4 steps deep, or more. In the present work we fix this memory depth at 3. This parameter has been shown to have important effect on the performance and can be one of the key parameters to be optimized in future work.

The task of the SODAS control system is to demonstrate efficient obstacle and hazard avoidance, in combination with goal orientation. Accordingly, a cruising FSM is implemented, called *cruise_XY_Z* which aims at directing SRR2K to a specified goal location [X, Y], with minimizing contact with hazard and obstacles.

We set the simple task to start from a corner and reach a goal position *GOAL_XY* specified at the start of the experiment. The straight road may be not the best when there are some rough areas where difficult to cross, or some (small) hills, which difficult to scale, etc. In this situation we expect that a properly trained SODAS would decide to take a path which avoids the difficult areas, or at least tries to do so. If proper learning and generalization took place by SODAS, one could change the terrain into a layout which SRR never seen before, still it should achieve good performance.

It is important to note that SODAS will not provide an absolute optimal decision, in general. Or at least this is not likely. Rather it may choose a sub-optimal path. But this in general would be more robust than a optimal path designed by a rule-based method.

The rover is at a given state at any instant of its operation, and it transits to a next state based on its present state and available input information. The schematic view of the used FSM with 6 states is shown in Fig. 3.

Cruise_XY_Z accepts two controlled variables *Angle_to_turn* and *Distance_to_go*. These variables are provided by SODAS through the cmd55 file. Note that a third variable *Desired_velocity* can be controlled as well. However, in the limited task for the present project, *Desired_velocity* was given a value of 10 cm/s and has not been changed for simplicity.

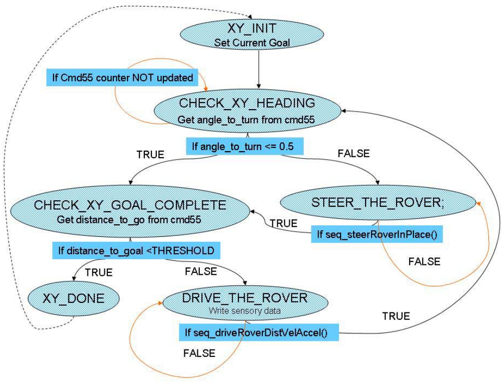

Figure 3. Finite State Machine *cruise_XY_Z* used for the SODAS navigation control

B. Learning and Control Algorithm

There are three phases of operation of SODAS: (i) learning phase; (ii) labeling phase; and (iii) testing phase. Here a brief description of the system is given. For details of the SODAS operation, see [39].

1. At the *learning phase*, SRR explores the environment and builds association between visual, IMU, and orientation sensory modalities. If it makes a good step during its random exploration, it gets a positive reinforcement signal and a Hebbian learning cycle is completed. Reinforcement signals are given by the IMU values in the case of visual channel, and by the goal position in the orientation channel; see Fig. 1. Hebbian association rule with negative learning rate is executed in the visual cortex module, if the IMU indicates excessive vibration in the tilt. In the orientation module (hippocampal model), positive reinforcement is executed if the rover moves towards the goal location.
2. During the *labeling phase*, certain activations from the SODAS model are collected as reference patterns. These patterns are collected from the Amygdala/ Enthorhinal cortex layer, which project to the action selection module. The selected patterns are activations representing correct motion in a given direction. For simplicity, we chose from the following possible actions: turn at +45 degree, turn at -45 degree, and move forward for a given distance. Concerning the length of the move, we use for simplicity discrete values 25 cm.
3. At the *testing phase*, the previously selected reference activations are then used for finding the right direction of the movement. During tests, SRR is placed at a selected position in the environment and is left to move on its own. At each step SRR captures the sensory data, extracts the main features, and passes on to SODAS. The activations generated from this test input are matched to the stored reference activations. A decision algorithm is used for action selection. We use either the best match, or the k-nearest neighbor voting scheme.

During the learning phase, a stereotypic behavioral pattern is used when an excessive level of surface roughness is identified via the tilt oscillation signals. High oscillations indicate that SRR hit a rock and started to drive through it. At this point we introduce the stereotypic movement*: 'Backtrack and Turn Away.'* As the forward movement step is 25 cm, we chose -50 cm for backtracking to make sure the rover leaves the obstacle area. Turning away allows the rover to face a new situation during the learning process.

IV. Results of Navigation Experiments

A. Experimental Goals and Strategy

In the framework of the present studies, we had limited time and limited access to the SRR2K test bed. Therefore, our goal has been to implement the reinforcement learning strategy and to demonstrate the feasibility of the proposed SODAS-based method for actual navigation and intentional control of the rover. Detailed tuning and evaluation of the navigation method is beyond the scope of the present work, and it remains a task for future studies.

A series of 32 experiments have been conducted over a period of a few weeks, depending on the availability of the equipment. Experiments had varying durations from a few minutes up to about ½ hour (approx 50 steps). About half of the efforts have been spent on calibration and on the development of the computational interface, as described in the previous section. In this section, we introduce some results on the associative learning, and demonstrate the operation of the trained SRR2K-SODAS navigation and control system.

B. Learning to Associate Sensory Modalities

In learning experiments, SRR2K is allowed to drive through the terrain. In these experiments the goal location is specified at the start of each run and SRR2K tries to drive to it. On its way it may meet an obstacle, which consists of some stones, which it can drive through. However, once it detects the obstacle through its tilt vibration signal (IMU RMS), it executes a *Backtrack and Turn* stereotypic behavior. At the same time a negative reinforcement act takes place. The aim of the experiment is to achieve that after several *Backtrack and Turn* events it would associate the visual image preceding the encounter with the following act of negative reinforcement, and should try to avoid it at the testing phase. In these experiments, no control action has been taken based on the eventual learned behaviors.

Fig. 4 shows a sequence of several such learning events. The upper frame of Fig 4 shows the average tilt oscillation level (IMU RMS, dash), and the maximum wavelet coefficient in the visual field (solid line). The lower frame shows the distance traveled at the give time step.

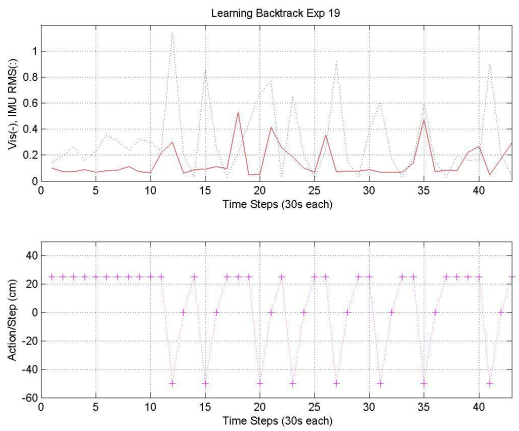

Figure 4. Example of learning sequence by SRR2K. Upper panel: average tilt (IMU) RMS – dashed line; maximum wavelet coefficient in the visual frame – solid line; Lower frame: action step taken by the rover. A sequence of 8 backtrack- and turn operations are seen.

The distance can be 25 cm if the rover moves forward, 0 cm if it turns, or -50 cm, when it starts a *Backtrack and Turn* behavior. Fig. 4 shows backtrack operations executed at time steps 12, 15, 20, 23, 27, 31, 35, and 41. At the same time steps the tilt RMS is indeed high, indicating the act of driving over the bump. The visual signal detects in most of the cases the obstacle in advance. In some cases, like time steps 15 and 30, the rover already drove into the bump, and the second RMS peak is likely due to its hind wheels driving through the bump.

C. Demonstrating Navigation by SRR2K

After several training sessions, the trained SODAS control system has been tested. The results indicate that SRR2K did learn to avoid obstacles, although its performance is not yet flawless. This is illustrated in Fig. 5. At the start of the session, the rover met some minor rocks, which it has identified as obstacles. Accordingly, it has conducted a sequence of learning cycles with *Backtrack and Turn* steps. These rocks were less significant and SRR2K touched them only slightly. From step 10 till 30 it conducts a successful navigation sequence with several turns, when it feels appropriate to avoid the obstacles. At the end of the session the rover does hit a major rock with one its wheels, based on the IMU oscillation readings. This event again triggered two consecutive learning sequences. At the end of the session, the rover successfully reaches the goal.

The results show the potential of the introduced navigation method. Clearly, further detailed optimization of the learning and control algorithm is required to get improved performance. At the same time, the goal of the present studies has been achieved. We have demonstrated that the introduced SODAS-based control system can indeed establish an association between sensory modalities through its self-learning dynamic algorithm. This algorithm is utilized by the rover to predict the result of its intended actions, and modify its decisions to avoid undesired consequences.

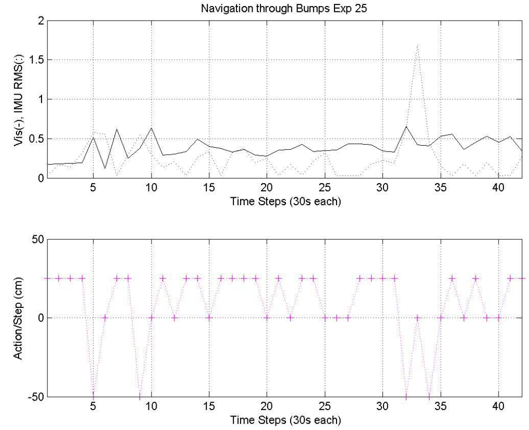

Figure 5. Behavior of SRR2K during a test run, while the learning is still active. Some minor rock initiated a learning cycle during time steps 5 to 10. Smooth navigation with correct turns is demonstrated until step 32, when the rover hit a larger rock. This again initiated an additional learning cycle.

V. Discussions and Concluding Remarks

In this work, a biologically-inspired control and navigation method (SODAS) has been introduced. The SODAS-based intentional control uses a dynamical system model, which tries to predict the consequences of the autonomous agent's action based on the environmental clues, in the context of its internal state. The control method has been implemented and its operation has been demonstrated on the SRR2K rover platform.

The central issue of this work is to study how the SRR-SODAS control system can build associations between various sensory modalities, in this case between visual, vibration, and global orientation sensing. Our calibration measurements showed that there is a time lag between an obstacle appearing in the visual field and the actual act of hitting it by consequent traversal. This shows that there is a potential of building the required associations. A successful association means that SRR2K would anticipate the act of hitting the obstacle and would take actions to prevent this from happening.

Formally, such associations can be created using a rule-based system. For example, one could develop a system to analyze the visual image, identify any obstacles, and take action to steer away from it. Clearly, this approach could be successful under certain limited conditions, like the ones given at the present SRR2K tests. However, such method would have very limited value, as any such rule should be re-calibrated in other situations, or when the conditions vary, e.g., light conditions, or surface roughness and composition.

Our suggested approach is more robust as it does not use a given, pre-defined rule system. Rather, the robot develops its own behavioral patterns and rules to achieve its goals. These behaviors can be continuously adapted as required by the changing conditions of the environment, or by changes (degradation) of structural components of the rover itself.

One can optimize the learning and testing performance of the SODAS-SRR2K system by tuning various control parameters. This is a time intensive task, which has been beyond the goals of the present work. Future studies are needed to properly tune the system and achieve improved performance in practical situations.

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