A Robust Neural Robot Navigation Using a Combination of Deliberative and Reactive Control Architectures

Dalia Marcela Rojas Castro, Arnaud Revel, Michel Menard

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D.M. Rojas Castro, A. Revel and M. Ménard *

Laboratory of Informatics, Image and Interaction (L3I) -University of La Rochelle
Computing Science Department -17000 - La Rochelle - France
e-mail: {dalia_marcela.rojas_castro, arnaud.revel, michel.menard} @ univ-lr.fr

Abstract. This paper proposes a hybrid neural-based control architecture for robot indoor navigation. This architecture preserves all the advantages of reactive architectures such as rapid responses to unforeseen problems in dynamic environments while combining them with the global knowledge of the world used in deliberative architectures. In order to take the right decision during navigation, the reactive module allows the robot to corroborate the dynamic visual perception with the *a priori* knowledge of the world gathered from a previously examined floor plan. Experiments with the robot functioning based on the proposed architecture in a simple navigation scenario prove the feasibility of the approach.

1   Introduction

Navigation strategies allowing mobile robots to autonomously travel from a starting point to a goal are extremely diverse [1]. Control architectures are the essential component of such navigation. They define the capacities of the robot to plan a path trajectory, to undertake autonomous decision-making and to execute the appropriate reaction according to the perceived environment information. Three types of control architecture approaches of mobile robots have been proposed in the literature: deliberative [2], reactive [3] and hybrid [4] [5].

   This paper proposes a hybrid control architecture where the robot emulates the cognition process of a human brain when navigating an unknown building by "reading" a map or a floor plan using its camera and "remembering" a sequence of signs to follow in order to reach its goal destination while overcoming the challenges presented in dynamic environments. Our approach addresses the control in a manner that is significantly different from existing hybrid architectures mainly in two ways. Firstly, the *a priori* global knowledge of the environment is gathered by the robot from a floor plan of the building and it is used to only corroborate the dynamic visual information instead of directly controlling the actions of the robot. Secondly, instead of using a complete motion path, this architecture makes use of navigation signs (and their expected sequence in the route), the associated directional implications of which may be learnt as a consequence of a stimulus-response model during navigation.

2 Hybrid Neural-Based Control Architecture

The overall architecture proposed in this paper (see Fig. 1) is based on the PerAc ("Perception-Action") architecture proposed by Gaussier and Zrehen [6] as an organized neural structure allowing learning of sensory-motor associations.

It follows the same neural mechanism of evolution by robot-environment interaction. However, unlike the PerAc architecture, it uses an *a priori* knowledge of the environment in order to corroborate the dynamic visual information perceived during navigation. Therefore, it is composed of two modules (Fig. 1): A deliberative module, corresponding to the processing chain in charge of computing a path plan by extracting a sequence of navigation signs expected to be found in the environment; and a reactive module, which integrates the said sequence information and constantly uses it in order to control online navigation. This latter reactive module is composed of two data streams corresponding to perception and action flows, similar to the PerAc architecture. The first level (dotted purple line region in Fig.1) uses a reflex mechanism that controls directly the robot's action based on the information extracted from the perceived input. The second level (dashed orange line region in Fig.1) uses a cognitive mechanism performing recognition of the aforementioned perceptive flow and allows learning of the associations between the recognition of a particular sign and the realization of a particular action.

2.1 Deliberative Module: Route planning and sign sequence

The global knowledge of the world is represented by a paper-based document (e.g. floor plan) that is placed in front of the robot's camera just once, before the navigation activity starts (Fig. 2a). It contains the important information to define a potential navigation trajectory. In this work, this information is represented by some navigation signs used as reference points that are expected to be seen by the robot in the real world navigation (Fig.2b). By means of computer vision methods, the robot is able to "read" the image of the floor plan acquired from its camera, generate an optimal plan to reach the goal, extract and memorize a sequence of signs arranged from the closest point to the furthest with respect to the starting point. This process is achieved through four main stages (Fig. 1) the details of which are omitted here for the sake of brevity, in favor of detailing the more relevant reactive module. Once the sequence of signs has been extracted, the robot is ready to start navigating the building as described in the following paragraphs.
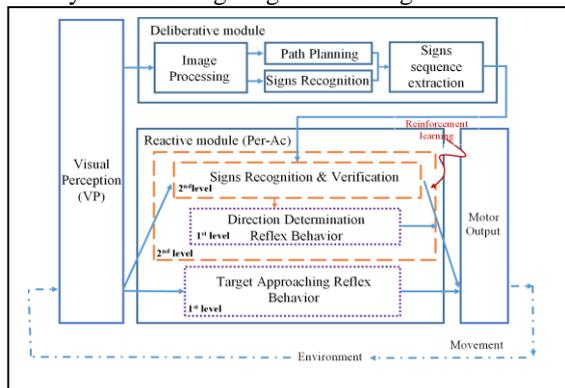

Figure 1. Schematic representation of the hybrid architecture
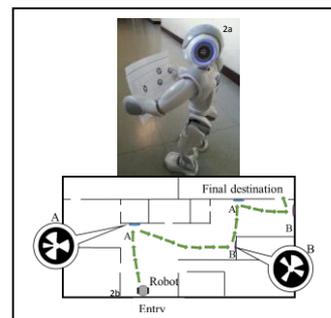

Figure 2. (2a) Nao robot reading the map; (2b) Generated route by following the navigation signs

2.2 Reactive Module: Real world navigation

This module is composed of two levels similar to PerAc. However, it has a nested PerAc architecture within its own second level, and hence, is composed of three layers (Fig.1). At the start of the exploration the robot may or may not know the meaning of each sign in terms of the instruction it represents with respect to way-finding. The architecture is designed such that if the sign is unknown or not detected at all, a "reflex" exploratory behavior gradually leads it to the correct direction and then the association between the sign and the movement performed is learnt (see 2.2.1 (b)). The learning is conditioned by a reinforcement signal which reflects the success or failure of the robot and whose information is transmitted by a modulation connection. Hence, if the same sign appears again and it has already been associated to a particular movement, the robot knows which direction to take and it executes the related movement (see 2.2.1 (a)).

Additionally, the architecture also performs a target approaching behavior when the robot is too far from a sign in order to be able to read it (see 2.2.1 (c)). Since the whole system works in parallel, a competitive mechanism decides on the best behavior (from among alternatives) for controlling the robot according to the stimulus received. Hence, the neural interconnection is done by either excitatory or inhibitory connections allowing or preventing the activation of group of neurons respectively.

2.2.1 Layers description

a) Signs Recognition and Verification (SRV):

Once the robot begins exploration, this level enables the robot to perform a movement based on the combination of the acquired static data (sign sequence) and the dynamic visual perception of the robot's camera. This layer is composed of six neural groups as shown in Fig.3. Each group has a number of neurons greater than the number of signs that can be recognized by the robot, each neuron representing a unique sign. The output direction group is composed of two neurons for left and right movements respectively.

As the robot interacts with its environment, dynamic visual information is constantly fed to the *Sign detection group*. However, this group is only activated if one or more signs appear in the robot's view activating their corresponding neurons. The *Sequenced sign group* stores the sequenced signs from the floor plan. The expected sign from the sequence activates its corresponding neuron and once the robot has approached it, the sequence is rescanned to obtain the next expected sign. The corresponding neuron of the *Sign merged detector group*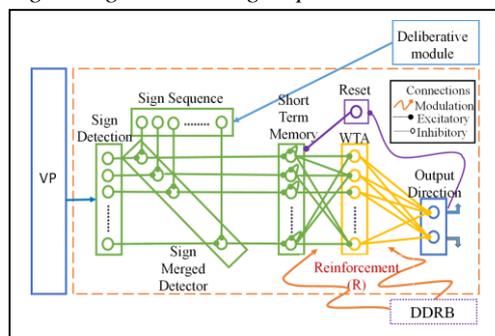 is then activated only when both inputting neurons (from the two neural groups mentioned above) are active. Then, the *Short term memory group* stores the activation value of the detected current sign in order to associate it, at a later stage, to the movement that would lead to the detection of the next sign. The *WTA group* enables the neuron with the highest activation value to stay active whereas all the others are set to zero by competitive "winner-takes-all" mechanism. The resulting activated neuron represents the current sign, to

Figure 3. Sign Recognition & Verification (SRV)

be associated to a particular action. The interconnectivity is made in such a way that it allows learning of the said association conditioned by the activation of a reinforcement signal set in the reflex level (see (b) below). Finally, the *Output Direction group* receives input from both layers (the current one and the Direction Determination Reflex Behavior layer (DDRB)).

b)   Direction Determination Reflex Behavior (DDRB)

This layer is in charge of making the robot explore the environment by rotating in its place (to its left by design) using small reflex movements, to look for the next expected sign in the pre-captured sequence and then learn the association between the sign and the movement performed. This occurs in one of the following cases:

1. The received visual input from the camera does not correspond to the expected sign. In this case, the robot continues to search for it using the aforementioned rotational reflex movements. If the sign is found, the SRV layer (explained above in (a)) and TARB layer (explained below in (c)) are activated.

2. The expected sign is detected but has not yet been associated with a specific movement. In this case, the robot searches for the next sign by rotational movements. Once this next sign is found, the angle of rotation undergone is allocated to the current sign as its associated movement in that direction (left by default). If this angle is greater than 180°, the movement associated is a turn in the opposite direction (right).

Thereafter, the reinforcement signal is activated to learn the association in the SRV layer. The DDRB layer is mainly composed of seven neural groups (Fig.4): The *Sign Detector* receives the input coming from the SRV group. Then, the reflex movement is triggered or inhibited by the *Trigger Reflex group*. The *Reflex Output Direction group* sends the information to the motor output to perform small leftwards rotational reflex movements. The angle of each rotational movement is stored in the *Memory Angle group* and then added to itself as many times as is required to find the next symbol. Once the symbol is found, the resulting angle is transmitted forward to the *Direction group* to be compared to a threshold and then re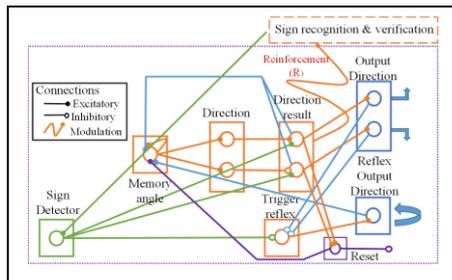set to 0 for the next calculation. The resulting comparison allows the activation of the neuron corresponding to the movement, either a left or right by excluding each other. Thereafter, the *Direction Result group* activates the neuron corresponding to the resulting movement as well as the reinforcement signal R (set to 1) in the *WTA group* of SRV. Finally, once R is set to 1, the association between the current sign and the movement is learnt in the *Output Direction group*.

Figure 4. Direction Determination Reflex Behavior (DDRB)

c)   Target Approaching Reflex Behavior (TARB)

This layer is triggered when the robot is far from the sign. It directs an approach towards the sign by keeping it in the center of the robot's vision. If, for instance, the sign is situated at the left side in the robot's visual space, the movement needs to be performed towards the left. It is important for the robot to approach the target sign to avoid

premature turns with respect to the intended point of turn for that sign. This layer is composed of the following three neural groups as shown in Fig. 5. Each group comprises of three neurons corresponding to a single movement each: walking to the left, walking to the right or walking straight ahead.

In the *Reflex sign position group,* each neuron has a position (x, y) in the robot's visual space so as to be compared to the position (within the same space) of the detected sign. They all behave as neural fields that can be calculated by a Gaussian function. The closer the neuron is in relation to the sign position, the higher the resulting value. All three values are sent to the *WTA group* that enables the neuron with the highest activation value to stay active whereas all the other neurons are set to zero. The *Reflex output position group* sends the resulting movement of the activated neuron to the motor output.
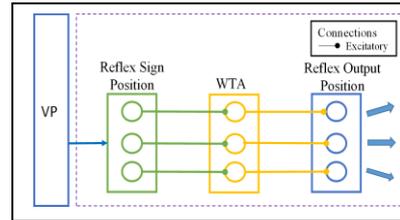

Figure 5.Target Approaching Reflex Behavior

2.2.2   *Convergence of layers*

The three layers described above converge towards the motor output group which comprises of six neurons corresponding respectively to six possible movements:
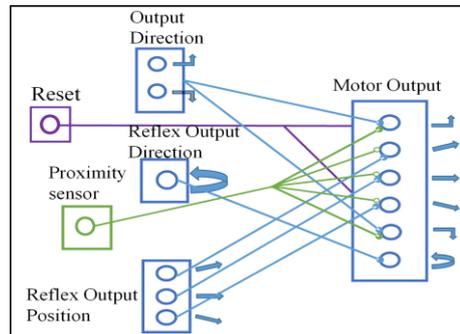

Figure 6. Convergence of layers towards Motor Output

turning left, turning right, walking left, walking right, walking straight ahead and turning left as a reflex movement (Fig.6). The activation of one excludes the others' depending on inhibitory and excitatory signal connections. When the robot is close to a sign (proximity sensor on), the activation of the reflex output position is inhibited and conversely if the robot is far from a sign, the direction movements are inhibited. The reset neuron inhibits the activation of the motor output group when it is activated by DDRB since the movement has already been performed by the reflex movement.

3   Verification Results

Fig. 7 shows a summary of results obtained (by following the path from Fig.2b) in the form of the activation of the output neural group corresponding to the six possible movements that can be performed by the robot (so far), over time. The movements were a result of either recognition, proximity or absence of any signs from the extracted sign sequence. The activation of the reinforcement signal allowing the association learning is also shown. In each of the (a, t) plots shown, a is the binary activation of each neural group or the reinforcement signal and t the time seconds in terms of a PerAc cycle. Overall, it was observed that while navigating the environment, the robot was

successfully able to perform the intended actions. For instance, when the robot was close to an expected but unknown sign, *'sign A'*, at t_8, it performed reflex movements from t_9 to t_{13} to search for the next sign, figured out the associated direction and learnt it at t_{14}. When it got close to the same sign at t_{32}, it was able to recall the learning and perform the associated movement.

4   Conclusions and Perspectives

A combination of reactive and deliberative architectures into a neural system for robot control navigation has been presented in this paper. As a result, a robot is capable of performing autonomous navigation, online learning of sensory-motor associations, parallel processing, decision-making and rapidly responding in environments prone to change. Implementation of the architecture in a simple indoor navigation scenario shows feasibility of this approach.

A potential drawback of the described implementation using the robot's camera is that the expected information might be partly occluded or not be visible at all. Consequently, the robot may get lost in the environment or be led to the wrong destination. A solution can be to implement principally the same architecture with other types of sensors to detect other relevant visual or non-visual

Figure 7. Output activation over time

cues in the environment. This would be possible by simply adding new layers without modifying the already in-built components or layers. Such a robust and complete architecture could even allow the robot to not only achieve its goal destination but also recreate an updated map according to the information assimilated from the environment.
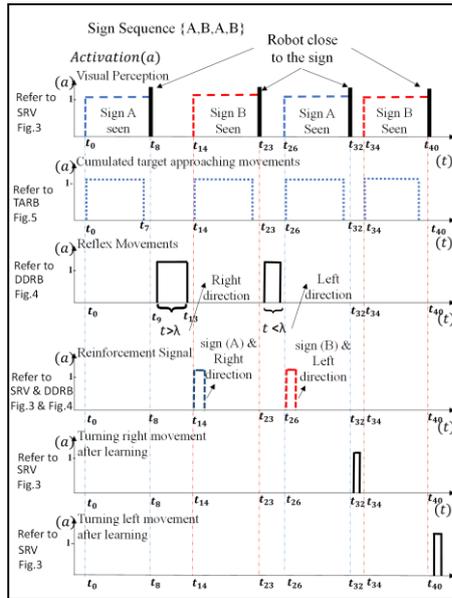
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