A Unified Model For Developmental Robotics

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Abstract

We present the architecture and distributed algorithms of an implemented system called NeuSter, that unifies learning, perception and action for autonomous robot control. NeuSter comprises several sub-systems that provide online learning for networks of million neurons on machine clusters. It extracts information from sensors, builds its own representations of the environment in order to learn non-predefined goals.

1. A need for a common framework

Several approaches and models propose developmental robot properties (Tijsseling and Berthouze, 2001, MacDorman et al., 2001). From a robotics point of view, all these properties should be implemented in a single system and the question of system integration must be addressed. We propose a multi-scale and distributed model which permits to address online perception, representation, goal learning, and skill acquisition. With this system, the robot acquires new capabilities by building new representations, starting from a very elementary predefined set, and by synthezising new actions (or skills) also using a very limited elementary set as a starting vocabulary. Learning and adaptation rely on an exploration process that enables to build and reinforce the representations and actions. These actions are the more rewarding in achieving the system's goals, which are also incrementally learned. No predefined structures are given to the system - except its general neural architecture. The classical symbol grounding problem (Harnad, 1990) is thus addressed.

System architecture is described in the next section, and an example of operation in section 3.

2. System Architecture

The global system has two main properties : *a)* the first is extraction of representations from the environment, and *b)* the second is action chaining to obtain the representations which produce the best global effect. The system is composed of seven functional subsystems as depicted in Figure 1 (Paquier and Chatila, 2002).

The system is structured in *slices* of connected Pulsed Neural Networks (PNN) based on a discrete integrate and fire model. PNN provide a level of description that allows to develop the learning process (Gerstner and Kistler, 2002), categorization and association, while avoiding combinatorial explosion. Within each slice's thickness, six neurons are connected to form *a column* which is the basic element of the system. The first three neurons of a column are responsible for information extraction and competition in the input stream, the fourth neuron is responsible for the persistence of detection and is the input to the next slices. The last two neurons are responsible for the scoring process and its diffusion in the global system.

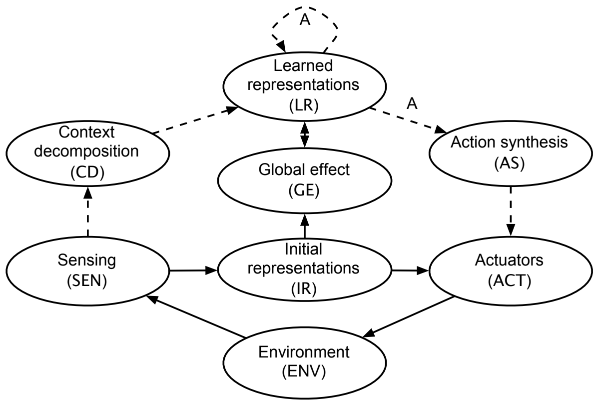

Figure 1: Global system and sensory-motor loops. Plain arrows are hard-coded pathways and dotted arrows correspond to learned pathways.

The functions of the seven subsystems are as follows:

- **Sensing** (SEN) is the input of the global system and is the frontier between the environment and the neural space. It is composed of maps of converter neurons between physical value and computable information wherein the potential values are static and dynamic "images" of the stimuli.
- **Initial Representations** (IR) is a neuronal structure which is the initial set of representation goals. Each neuron in IR can be activated by SEN, and the result of this activation has a predefined effect on the criteria satisfaction (see GE next). IR can be considered as the initial position in the *representation/score* space. The system behaviour will grow from this point.
- **Context Decomposition** (CD) can be defined as the categorization engine. It extracts all the high-level features that could be used to describe the environment. It is

composed of a multilayer network of maps in a pyramidal structure. The layers of CD build representations by detecting regularities in the preceeding ones.

- **Learned Representations** (LR) receives inputs from CD and itself. This sub-system has the properties of an associative memory. It is responsible for learning of new skills and determines the global system behaviour. Each neuron of LR is connected to GE for criteria evaluation. We define representations as the set of active columns in LR at time t.

- **Elementary Actions and Action Synthesis** (AS and ACT) are the action sub-systems. AS produces combinations of elementary actions. Its outputs are connected to ACT. ACT is the interface between the neuron/pulse space and the environment. It is a one-layer set of maps where each map drives a degree of freedom of the effectors in a multi-scale way.

- **Global Effects** (GE) is a scoring system which associates a value with each representation. We call effects the score obtained through a representation. GE represents the criterion the system wants to maximize. When the effects of a representation are negative the system will produce actions to increase the criterion value.

3. Developmental properties

The system is able to detect spatial and temporal invariants, and to produce new actions. We will provide here an example of detection of spatial invariants. Patterns are extracted from images and grouped in classes according to an invariance criterion - which will be related to shapes in the environment. SEN neuron potentials are composed of images of projections of these shapes. CD extracts what is common or different among the features that compose them.

Figure 2 shows a simple result where 3 distinct objects are presented to the system. After decomposing the image into elementary features, three LR maps are learned to detect and localize each particular object. This example only uses the spatial competition property. The images of potentials are decomposed by applying groups of competitive filters systematically and simultaneously on each part of the images. The layered architecture of CD permits to repeat this process across the structure so that the neurons at the top of CD correspond to a receptive field as large as the whole image. At this level of representation, input images have been diffracted in the sub-system, decomposed in spatial frequencies and pattern contents, and recomposed in more complex structures. This "decomposition and recomposition" evolves across time and converges toward a stable state. All the learned weight kernels are based on the image frequencies and feature contents. The activity of the high end neurons of CD provides this distributed representation of the environment.

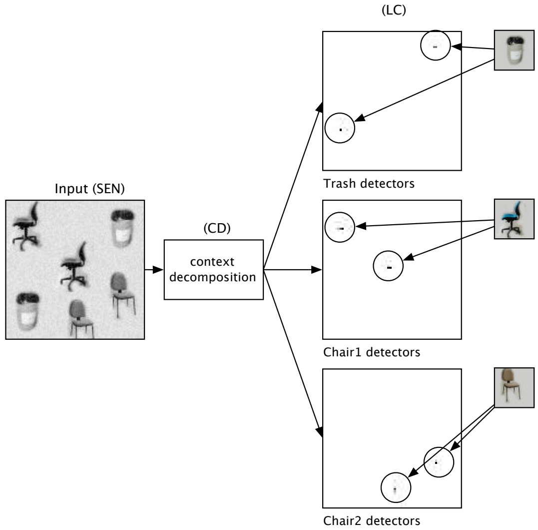

Figure 2: Simple example of spatial competition among neurons of different maps of the same layer. In LR layer, burst state are represented by grey level. White means no discharge. The system is able to discriminate and localize the two kinds of chairs and the trash bin from 128x128 input image. In this example, the system includes 20 480 neurons and 13 922 304 synapses. The extraction stability is obtained after 500 time steps (less than a minute on SunBlade 100 workstation) while recognition duration is much smaller (about 12Hz in the same conditions).

4. Conclusion

Implementation of this architecture is in progress and first experiments are underway with a Nomadics XR 4000 and a six-legged robots for the elaboration of new behaviors.

References

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