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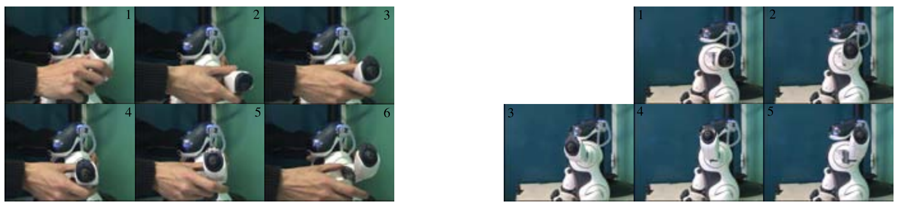
Learning From Social Interaction

ABSTRACT

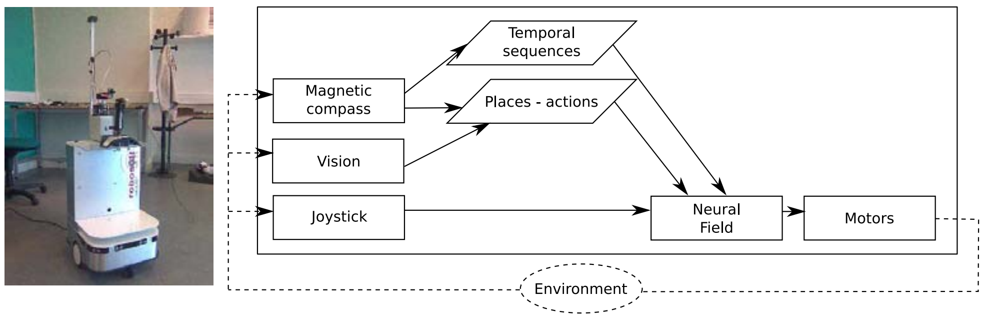
Neuronal architectures are developped to understand how social interaction can allowed autonomous robot to learn more and more complex tasks.
We propose to learn different sensori-motor associations depending on the available proprioception signal and on the kind of interaction. New behaviors emerge from the dynamic of the interaction, as shown in the imitation of a sequence of actions or imitation of emotional expressions.
These mechanisms are crutial as they allow different higher level learning, as complex sequence of displacements in the case of a mobile robot and could lead to different type of interaction resulting of social referencing (emotional association to an object).

1 Learning sequences of actions by imitation



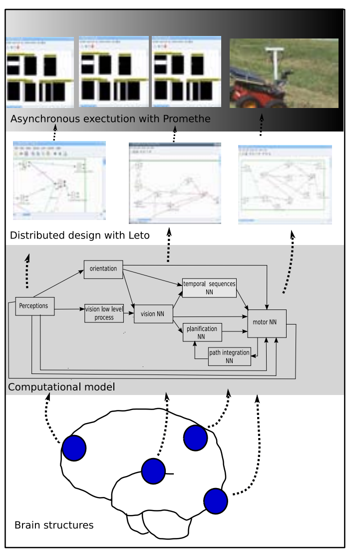
- From a simple sensory-motor architecture, a behavior of immediate imitation emerge.
- When the robot imitates, the neural network learns online the succession of the joints orientations thanks to the motors feedback informations of its leg [1].
- Thanks to the internal context generated by CTRNN oscillators, the neural network is able to learn complex sequences (sequence with same repeated state(s)).
- To initiate the reproduction of the sequence, we give the first orientation. From this starting state, the neural network predicts the next orienation. Hence, the robot reproduces step by step the sequence autonomously.

2 Learning complex sequences of displacements



A mobile robot learns a new behavior as a sequence of actions related to spatial (places-action associations) and temporal (complex sequences) constraints [2].

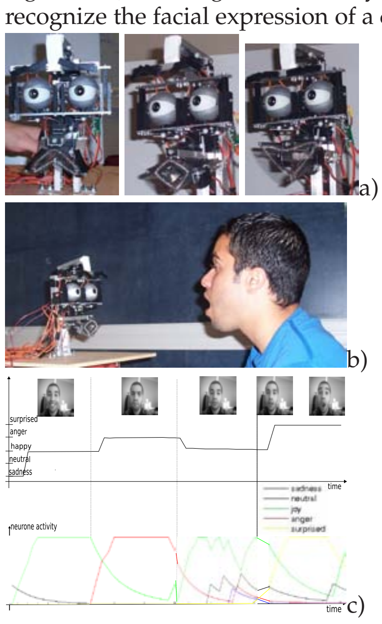
3 Design of a distributed real-time artif cial neural network



In the field of epigenetic robotics, our interest is to study the emergence of higher level behaviors, from the combination of low level building blocks [3].
To execute an application on several processing units, the different neural networks (NNs) need to communicate. To do so, Metaleto allows a global view of a distributed NN and it generates network file to execute a distributed application with Promethe.
In the frame of robotic control, some parts of the neural architecture are critical and must deliver a reliable and predictable signal with respect of time constraints. Our simulator of NNs Promethe uses a mechanism of RT (Real Time) tokens to schedule groups of neurons and to respect time constraints.
Since emerging behavior is our major interest, we do not use a priori solutions fixing or selecting the priority of the loops. In our models, we prefer to use intrinsic selection of the action according to dynamical equations simulating a continuous neural field of neurons.

4 Emotional expressions imitation

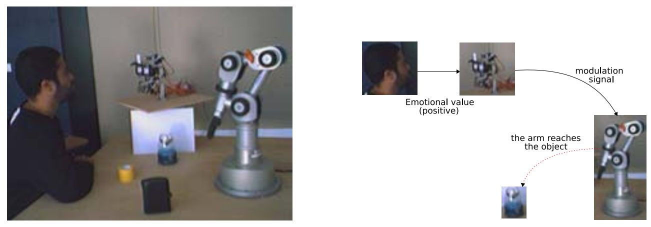
We are interested in knowing how a robot head can learn to recognize facial expressions without explicit supervision. Our starting point is a mathematical model (cognitive system algebra [4]) showing that a sensory-motor architecture is able to express its emotions and to recognize the facial expression of a caregiver.



In the first phase of interaction, the robot produces a random facial expression as sadness, surprise, happiness (a) and if and only if the human mimicks the robot expression, the robot learns it by associating its proprioception to the human face vision [5].
In a second phase of interaction (b), the robot can mimic the human partner facial expressions, resulting in an imation behavior.

We show typical temporal activity (c) during the time that the robot reproduces the recognized facial expression
Success rate: happiness: 86%, anger: 66%, surprised: 51%, sadness: 48%, neutral: 36%
Global performances between 55% and 60% (statistical results) but results of the online human/robot interaction are more convincing.

5 Towards a social referencing



The robot uses its partner facial expression to adapt its behavior in ambiguous situations.
As the robot head recognizes the facial expression of the caregiver, it controls the artificial arm actions (reinforcing learning) :
- the object is reached (for manipulation,. . .) if associated to a positive emotional value
- the object is avoided if associated to a negative emotional value.

Conclusion

- No need of partner pre-identification, but use of perception ambiguity : the two partners are one dynamical system
- Imitation is a dual mechanism : favors learning and is a way of communicating
- Importance of social interaction : brings new insights in robot development and learning

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