

A new approach for learning postures: an imitation game between a human and a robot

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Abstract

In this paper, we investigate a sensory-motor architecture allowing a robot to learn to recognize postures. The learning is performed without a teaching signal that associates a specific posture with the robot's motor internal state. Our architecture assumes that the robot initially performs postures, then the human imitates them. An on-line learning scheme without an explicit reward or ad-hoc detection mechanism or a formatted teaching technique is proposed. Investigations on how a "naive" system can learn to imitate correctly another person's posture during a natural interaction motivate the current research work.

1. Introduction

In recent years, there has been a growing interest for Human-Robot interaction. Robotic experiments showed impressive results. However, some robotic experiments use ad hoc engineering strategies with a-priori information. Introducing learning processes will allow to design autonomous robots. In the case of rich interactions, we believe the robot's behavior must be investigated in a developmental perspective to avoid the symbol grounding problem [Masahiro, 1970] (a human expert must provide knowledge to the system).

In this paper, we will focus on learning new behaviors through imitation game between a human and a robot (Fig. 1). Imitation is an interesting solution to develop autonomous robots, since imitation reduces the search space of the learner and facilitate interaction (it is a very intuitive and natural way to interact). As a result, in the field of robotics, imitation is often considered as a powerful behavior corresponding to the ability to learn by observation [Kuniyoshi, 1994], [Schaal, 1999], [Calinon et al., 2007], [de Rengervé et al., 2010],

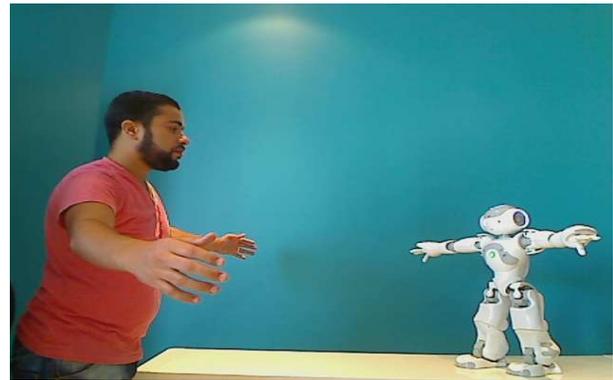


Figure 1. Example of a typical human / robot interaction game (here, the human imitates the robot)

[de Rengervé et al., 2011]. For example, a robot can combine known actions to reproduce a behavior that is done by somebody else. This notion of learning by observation is very close to the notion of "deferred imitation" intensively described in developmental psychology [Piaget, 1945]: the ability of a child to reproduce an observed task but in a different context, for example spatial and temporal.

In this paper, we will use the imitation as a communication tool: the caregiver communicates with the robot through imitation. [Nadel, 1999] showed that the imitation is a communication function. In a previous study [Boucenna et al., 2010], we also showed that imitation is a communication tool for online facial expression learning and recognition. Our experiments showed that a robotic head can autonomously develop the facial expression recognition without having a teaching signal. Our starting point was a mathematical model that shows that, if the baby uses a sensory motor architecture for a recognition of a facial expression, then the parents must imitate the baby's facial ex-

pression to allow on-line learning [P. Gaussier, 2004]. The baby-mother interaction are usually considered as a relevant framework. A newborn or infant has a set of expressions that are linked with his/her own internal state, for example crying and a sad face when he/she needs food or a happy face after being fed. [Meltzoff and Moore, 1977] show that infants between 12 and 21 days of age can imitate both facial expressions and gestures. Learning to recognize facial expressions without a teaching signal that allows the association between what is perceived by the robot and his internal state is challenging (e.g., the vision of "happy face" and an internal emotional state of happiness [G. Gergely, 1999]). This issue is investigated through robotic experiments [Boucenna et al., 2010]. In this paper, we show that, as the facial expression recognition problem, posture recognition can autonomously be learned with the help of the sensory-motor architecture.

To test our model, the following experimental protocol was adopted: In the first phase of the interaction (learning phase), the robot produces a random posture (4 basic postures and a neutral posture: see fig. 2) for 2s; then, the robot returns to a neutral posture for 2s to avoid human misinterpretation of the robot posture (the same procedure is used in psychological experiments). The human subject is asked to imitate the robot. After this first phase, which lasts between 2 and 3 min according to the subject's "patience", the robot must imitate the posture of the human partner.

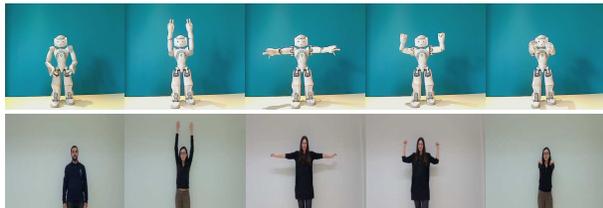


Figure 2. The robot and the human produce the 4 basic postures and a neutral posture.

2. Neural Network based on a sensory-motor architecture

2.1. Overview

In this section, we describe a sensory-motor architecture allows to learn, to recognize and to imitate postures. The visual processing allows to extract local views (Fig. 4), then each local view is learned by the *VF* group (visual features), and the *MISP* (motor

internal state prediction) group learns the association between the visual features and the postures (Fig. 3). This architecture can solve the posture recognition problem if and only if we assume that the robot produces first posture according to his/her internal state and that next the human partner imitates the posture of the robot allowing in return the robot to associate these postures with his/her internal state.

Traditional HRI architectures assume person local-

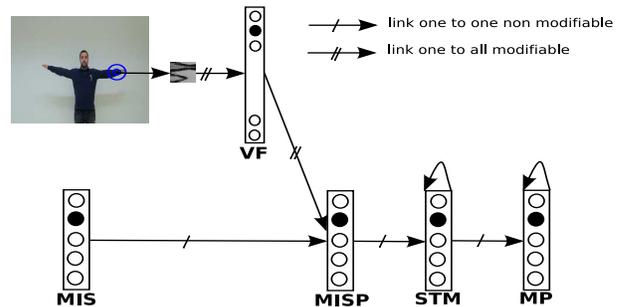


Figure 3. The global architecture to recognize postures and to imitate postures. Visual processing allows the extraction of sequential local views (the circle corresponds to a focus point). The *VF* group (local view recognition) learns the local views (each group of neurons, *MIS*, *MISP*, *STM* and *MP*, contains 5 neurons that correspond to the 4 postures plus the neutral posture).

ization and then, posture recognition is performed on the normalized image. In this case, the quality of the results is highly dependent on the accuracy of the person localization (the generalization capability of the N.N. can be affected). From the perspective of autonomous learning, avoiding any ad hoc framing mechanism appeared to be an important feature. Our solution consists of skipping the framing step to directly use all of the most activated focus points in the image.

2.2. Focus points detection

The visual system is based on a sequential exploration of the image focus points. A gradient extraction is performed on the input image. A convolution with a Difference Of Gaussian (DOG) provides the focus points. Last, the local views are extracted around each focus point (Fig. 4). However, there is no constraint on the selection of the local views (no framing mechanism). This scenario means that many distractors can be present such as objects in the background but also non relevant parts of the human body.

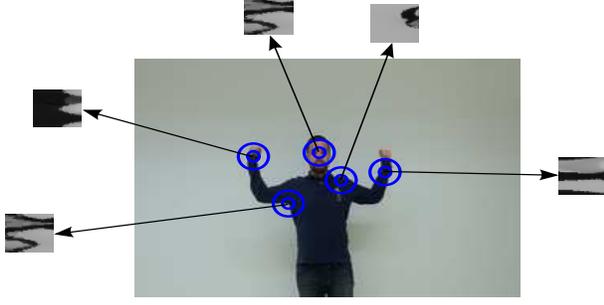


Figure 4. Visual processing: This visual system is based on a sequential exploration of the image focus points. A gradient extraction is performed on the input image. A convolution with a Difference Of Gaussian (DOG) provides the focus points. Last, the local views are extracted around each focus point (the arrows show the local views).

2.3. Visual features

The fig. 3 shows the sensory-motor architecture which is able to learn, to recognize and to imitate postures. The extracted local view around each focus point is learned and recognized by a group of neurons VF (visual features) using a k-means variant that allows online learning and real-time functions [Kanungo et al., 2002] called *SAW* (Self Adaptive Winner takes all):

$$VF_j = net_j \cdot H_{\max(\gamma, \overline{net} + \sigma_{net})}(net_j) \quad (1)$$

$$net_j = 1 - \frac{1}{N} \sum_{i=1}^N |W_{ij} - I_i| \quad (2)$$

VF_j is the activity of neuron j in the group VF . $H_{\theta}(x)$ is the Heaviside function¹. Here, γ is a vigilance parameter (the threshold of recognition). When the prototype recognition is below γ , then a new neuron is recruited (incremental learning).

\overline{net} is the average of the output, and σ_{net} is the standard deviation. This model allows the recruitment to adapt to the dynamics of the input and to reduce the importance of the choice of γ . Hence, γ can be set to a low value to maintain only a minimum recruitment rate. The learning rule allows both one-shot learning and long-term averaging. The modification of the weights (W_{ij}) is computed as follows:

$$\Delta W_{ij} = \delta_j^k (a_j(t) I_i + \epsilon (I_i - W_{ij}) (1 - VF_j)) \quad (3)$$

1. Heaviside function:

$$H_{\theta}(x) = \begin{cases} 1 & \text{if } \theta < x \\ 0 & \text{otherwise} \end{cases}$$

with $k = \text{ArgMax}(a_j)$, $a_j(t) = 1$ only when a new neuron is recruited; otherwise, $a_j(t) = 0$. Here, δ_j^k is the Kronecker symbol², and ϵ is the adaptation rate for performing long-term averaging of the stored prototypes. When a new neuron is recruited, the weights are modified to match the input (the term $a_j(t) I_i$). The other part of the learning rule, $\epsilon (I_i - W_{ij}) (1 - VF_j)$, averages the already learned prototypes (if the neuron was previously recruited). The more the inputs are close to the weights, the less the weights are modified. Conversely, the less the inputs are close to the weights, the more they are averaged. The quality of the results depends on the ϵ value. If ϵ is chosen to be too small, then it will have only a small impact. Conversely, if ϵ is too large, then the previously learned prototypes can be unlearned. Because of this learning rule, the neurons in the VF group learn to average the prototypes of the postural features (for example, an arm).

2.4. Classification

Distractors can be learned on VF . The figure/ground discrimination can be learned because the local views in the background will not be statistically correlated with a given posture. In this case of interaction, the distractors are present for all of the postures, and their correlation with an internal motor state will tend to zero. Only the local views on the person (Fig. 3) correlated with a given robot posture will be reinforced. The use of the Widrow and Hoff rule (derived from a least mean square (LMS) optimization) will learn correctly if, during the period that is allowed for the exploration of one image, sufficient focus points can be found on the person (Fig. 4). In our network, The Internal State Prediction *ISP* associates the activity of the visual features VF with the current motor internal state *MIS* of the robot (a simple conditioning mechanism using the Least Mean Square (*LMS*) rule [Widrow and Hoff, 1960]). The modification of the weights (w_{ij}) is computed as follows:

$$\Delta w_{ij} = \epsilon \cdot VF_i \cdot (MIS_j - MIS_j) \quad (4)$$

STM is Short Term Memory used to sum and filter over a short period (N iterations), and the motor states $MISP_i(t)$ associated with each explored local view are as follows:

$$STM_i(t+1) = \frac{1}{N} \cdot MISP_i(t+1) + \frac{N-1}{N} \cdot STM_i(t) \quad (5)$$

2. Kronecker function:

$$\delta_j^k = \begin{cases} 1 & \text{if } j = k \\ 0 & \text{otherwise} \end{cases}$$

Here, i is the index of the neurons; for example, $MISP_i$ corresponds to the i^{th} motor state ($0 < i \leq 5$).

Arbitrarily, a limited amount of time is fixed for the visual exploration of one image, to obtain a global frequency of approximately 10 Hz (100 ms per image). The system can analyze up to 10 local views on each image (the system usually succeeds in taking 3 to 4 relevant points on the person). This small number of views is sufficient to learn the different postures and to allow real-time interactions.

The control of the robot posture is performed via the MP group. The highest activity of the MP_i triggers the i^{th} posture because of a WTA. For increased robustness, MP also uses a short-term memory (giving more importance to the present than to the past), with $\beta = 1$ and $\alpha < 1$ ($\alpha = 0.8$):

$$MP_i(t+1) = \beta.STM_i(t+1) + \alpha.MP_i(t) \quad (6)$$

3. Results

The online learning can involve specific problems. For example, the human reaction time to the robot postures is not immediate. This time lag can greatly disturb the learning process. If the robot learns the first images, which are associated with the human's previous posture, then the previous posture is unlearned. The presentation time of a given posture must be long enough for the first images to have expired. In spite

				
80%	86%	74%	51.4%	77%

Figure 5. The success rate for each posture. A total of 7 persons interacted with the robot head. During the learning phase, these humans imitate the robot, and then the robot imitates them.

of this problem, the incremental learning is robust, although the number of human partners increases (7 human partners). The fig. 5 shows the success rate of the posture recognition when the robot learned with 7 human partners for 5 specific postures. Yet, the introduction of a short term memory (STM) at the motor level (for the triggering of posture) allows to obtain quite convincing results at the price of a small hysteresis in the decision process. The fig. 6 shows a natural interaction between the robot and the caregiver. This figure shows a caregiver which performs postures and the temporal activity of the neurons associated

with the triggering of the different postures when the robot imitates the human. In spite of this hysteresis, the system maintains a real-time interaction because the system can analyze 10 images per second (the system can analyze up to 10 local views on each image).

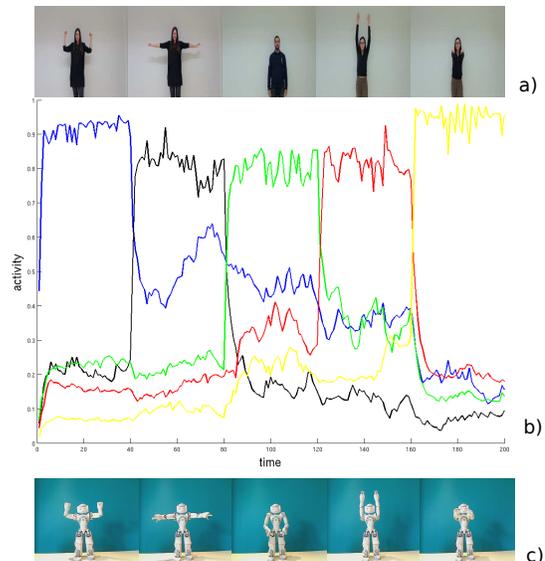


Figure 6. Result of posture recognition in the context of imitation. a) caregiver performs a posture. b) Temporal activity of the neurons associated with the triggering of the different postures when the robot imitates the human (after learning). c) the robot imitates the caregiver's postures.

4. Conclusion

In this paper, we showed that the robot is able to learn, to recognize and to imitate a number of specific postures. The goal of these experiments is to show that our architecture can be generalized to several tasks (for example, facial expression recognition [Boucenna et al., 2010], joint attention [Boucenna et al., 2011], or posture recognition). Our approach can enable autonomous learning through interaction, if the robot produces and, then the human partner imitates the robot. We can suggest the robot/human system is an autopoietic system [Mataruna and Varela, 1980] in which the imitation is an important element to maintain the interaction and to allow the learning of more and more complex skills.

In futur studies, we want to develop a model that is able to categorize a set of motor commands (motor commands for different articulations; for example,

shoulder, elbow, knee) rather one category per posture. Accordingly, the robot can perform a significant number of rich postures. A postural state can be obtained by the categorization of the motor states (after several reproductions of the different gestures). These futur models will improve the interactions between a robot and a human. Moreover, to improve the human robot communication, we want to build an architecture that integrate several capabilities (e.g., posture, emotion, and prosody) [Delaherche et al., 2012].

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