The Role of the Caregiver's Responsiveness in Affect-Grounded Language Learning by a Robot: Architecture and First Experiments

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***Abstract*—Most computational models of language development adopt a passive-learner view and disregard the important role that motivation and affect play in the development of communication. In this paper, we present a motivation-grounded, active learning robot model of language acquisition that relies on social interaction with a caregiver. The robot learns multiple associations—between words and perceived objects, and with its internal needs—allowing it to have a "meaning potential" of the acquired language, in line with the functionalist view of language theory. We evaluate the model experimentally and with different levels of caregiver's responsiveness to study the impact of external factors on language acquisition.**

I. Introduction

Affects and motivation play an important role in the development of communication. Typical observation in infant's development shows that communication is used as a mean by infant to convey functional meanings even before they master adult's language [1]. For example, communication can be a way to obtain a desired object by requesting it from an adult, or to strengthen a social bond. To give the robot this ability to learn language in this functional way, we endow it with a modular architecture able to learn multiple associations grounded in internal motivations.

II. Proposed approach and method

The overall architecture is shown on Fig.1. The formalism is related to the sensory-motor PerAc neural architecture [2] and consists of three modules: the motivation, visual perception and phonological modules.

The **Motivation module** (fig.1.A) modulates the robot's internal motivation as a function of time and visual perception (fig.3a) [3], [4], [5]. Each internal need is modeled by a homeostatic variable that decreases over time and increases when the need is fulfilled. The robot drive $d_i(t)$ is defined as the difference between the current homeostatic variable and its optimal value. The robot's motivation to satisfy a need depends on the related drive (internal factor) and the intensity of the stimulus (external factor) that can satisfy it [6]:

$$m_i(t) = d_i(t) + d_i(t).s_i \tag{1}$$

The stimulus s is estimated by the visual perception module. The **Visual perception module** (fig.1.B) allows the robot to perceive its environment. We used an online incremental learning method, similar to Kohonen's map [7], called SAW (Self Adaptive Winner). In this method, when the robot detects a new object, the extracted key point descriptors are stored in a visual feature matrix VF as follows: each new descriptor is compared to those already stored in VF, if the similarity is below a fixed threshold, the most similar descriptor is replaced by the mean of the two, otherwise the new descriptor is recruited directly to the VF matrix.

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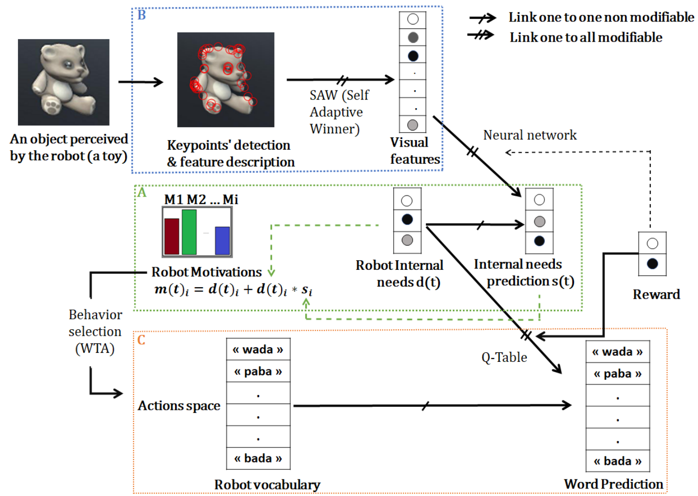


Fig. 1: The overall architecture consists of three modules: A. The motivation module, B. the visual perception module and C. the phonological module.

The **Phonological module** (fig.1.C) of the robot is composed of a vocabulary of two-syllable words, corresponding to 10 of the most frequent syllables of an 8-month-old infant [8], and a text-to-speech unit that allows the robot to vocalize its words.

Learning the associations between modules

Our model learns the associations between each pair of these modules. The goal is for the robot to be able to say a word when it is in a given internal state, to learn to name the objects present in its visual field and to know which internal need each object is able to fulfil.

The **association visual perception-motivation** is realized by training a neural network - which have the VF matrix as input - to predict the name of the detected object and which internal need can be satisfied by it. The synaptic weights update of this neural network follows the Widrow-Hoff rule [9].

For the second **association motivation-phonological modules**, we extend the RL approach proposed by [10]: in this method, each robot's internal needs can be satisfied with a specific object. The robot starts by randomly producing a word when one need outweighs the others, the caregiver -who does not have access to the internal need of the robot- reacts to the robot's vocalization by selecting an object and handing it to the robot. If the given object satisfies the robot's need, the motivation related to this need decreases, a reward of +1 is given to the robot which expresses its satisfaction with a happy

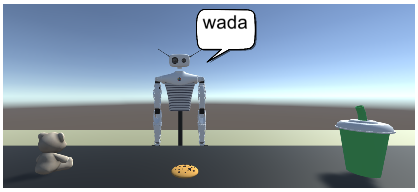
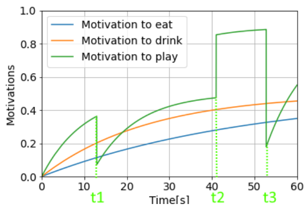
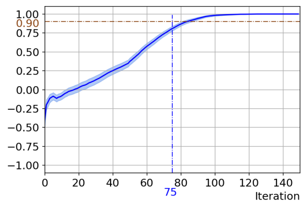


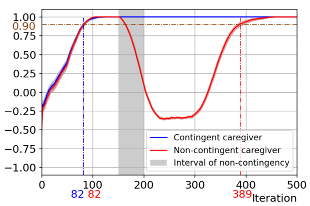
Fig. 2: Experimental setup.



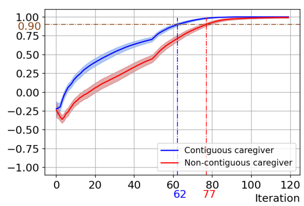
(a) Evolution of the robot's motivations. A drink was presented at t2, which increased the motivation to drink. At times t1 and t3, the caregiver gave the robot a toy, reducing the motivation to discover



(b) Evolution of average reward, convergence is reached after 75 interactions between the robot and the caregiver



(c) Evolution of average reward with contingent and non-contingent caregivers between the iterations n=150 and n=200



(d) Evolution of the average reward in the case of a contiguous and a non-contiguous caregiver

gesture, otherwise the word receives a reward of -1, which decrease the probability of reusing the word in this context, and the robot expresses its dissatisfaction. In RL, this problem is formulated as a contextual multi-armed bandit problem.

III. Experimental setup and Results

To test our model, we used the humanoid robot Reachy with the Unity simulation environment (fig.2), the robot has three internal needs: hunger, thirst and curiosity, these needs can be satisfied by objects present in its scene. When the robot express its need by a word (from its vocabulary 10 words) a human caregiver gives it one of the objects. The robot can express its satisfaction or frustration by putting its antennae up or down.

The average of the rewards is used as an evaluation metric (at each time step n, it is computed on the previous 50 values). The convergence time is defined as the number of iterations needed to reach 90% convergence. The results were calculated on the average of 100 repetitions of each experiment.

The results show the convergence of the moving average reward (fig.3b). Reaching convergence means that the robot has learned to choose consistent words that depend on its internal needs, and that the robot is understood by the caregiver, which allows it to obtain the desired objects. Table I shows the association between the robot's vocabulary and the internal needs; after learning, each need has only one word with a max Q-value, which confirms the convergence.

Effects of the caregiver's responses on language learning

	"wada"	"naba"	"maba"	"daba"	"paba"	"bada"	"bama"	"babe"	"waba"	"wama"
"Hunger"	-1	-1	2	0	-0.5	0	0	0	0	-1
"Thirst"	0	-1	-1	0	0	-1	0	0	2	0
"Curiosity"	-1	-1	-1	-1	-1	-1.25	-1	2	-1	-1

TABLE I: Q-table of the association between the robot vocabulary and its internal needs

To study the impact of the caregiver‘s responses on the robot language learning, we focus on two aspects of responses: contingency and contiguity. In child language learning, parent responses are *contingent* and *contiguous* when they are *conceptually* and *temporally* dependent on the child's communicative actions, respectively [11]. These both aspects of parental responses facilitate early infant language development [11]. We model a low level of contingency by a caregiver that chooses objects at random, regardless the robot feedback and the pronounced word. Contiguity is modeled by a caregiver who takes into account the temporal evolution of motivations when making a guess. Fig 3c and 3d show that the contingency and contiguity of the parental responses can contribute to the stabilization and acceleration of the learning.

IV. Conclusion

We have presented a robot model of language learning inspired by how children learn language through natural interactions with a caregiver. The association of each word with a need, rather than being a simple label paired with an object, is consistent with the functionalist view of language acquisition. Our model was validated in experiments testing the effect of a caregiver's responsiveness on the robot's language learning. The results are in line with infant studies on the influence of parental responsiveness on language acquisition [11]. In future work, we envisage to extend the motivational module with new emotional and affective states, in order to increase the number of meaningful words in the robot's vocabulary, and to ground the modeling of the more advanced functions of language.

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