

Clarifying the MM architecture

Alexis Jacq

I. REMIND OF THE FRAMEWORK

A. Justification of the approach

A first intuition for mutual modelling (MM) is to assume that all agents have the same architecture. In [1], Breazeal shows a MM-based reasoning where the robot uses its own architecture to model other agents. We can imagine a second level of modelling where the robot recursively attribute to other agents the mutual modelling ability. But that can create an infinite recursive loop: the agent then models the robot that models the agent etc. Another reasons to avoid an infinite recursive approach is that different agents must have different behaviours: in similar situations, they do not necessary take similar decisions.

We propose a different approach of modelling, where we define two orders of agent's model: the **first-order-agents** concern direct representations of agents by the robot (for example the child), while the **second-order-agents** concern the representation of agents by agents (for example the robot-perceived-by-the-child). Modelling second-order-agent like the robot-perceived-by-the-child, helps to model how the child perceives the robot, e.g. to make sure the child understand that the robot is learning from his demonstrations. We can as well define **nth-order-agents** with a higher level of theory of mind. But taking into account high levels of mutual modelling would be difficult to process in real time. Unlike the epistemic logic, our proposed framework will not take into account infinite regress [2] of mutual modelling.

B. Notations

$M_R[A]$ stands for the **model (built by the robot R) about the agent A** (first-order-agent). $M_R[A,B]$ stands for the **model (built by the robot R) about the agent B perceived by the agent A** (second-order-agent). As said above, we limit our approach to 1st and 2nd order of modelling. In a two-agents interaction (the child and the robot) we will focus on three models: $M_R[C]$ (the model about the child), $M_R[R]$ (the model about the robot) and $M_R[C,R]$ (the robot perceived by the child). It would be also interesting to study $M_R[C,C]$, the model about the child perceived by himself in order to play with his self-confidence. But detecting differences between $M_R[C]$ and $M_R[C,C]$ seems difficult with the current abilities of the robot.

As models are dynamic, $M_R^t[A]$ represent the model about an agent A at time t .

II. MUTUAL UNDERSTANDING

Given those three models ($M_R[R]$, $M_R[C]$ and $M_R[C,R]$) the robot must be able to detect misunderstandings. A misun-

derstanding of an agent A by the robot can be formalised as a error between what is actually in the mind of the agent (we can call it $\Phi[A]$) and the model built by the robot: $\Delta(\Phi[A]; M_R[A])$. But if A is human, $\Phi[A]$ is inaccessible to the robot. In order to maintain a mutual understanding, humans [3] (and monkeys [4]), use predictions of others' behaviours. A bio-inspired approach would be to make, at time t , a prediction $P_R^{t+1}[A]$ of the model. Then, at time $t+1$, the robot can compute a **prediction error** $\Delta(M_R^{t+1}[A]; P_R^{t+1}[A])$ in order to detect such a misunderstanding. This idea rely on the assumption that the better are the predictions of a model, the better the model fits the reality. Then, the dynamic of the model can be updated according to the resulting error of prediction. This rule can be used with $M_R[C]$ and $M_R[C,R]$.

Another type of misunderstanding concerns the comprehension of the robot by the child: using the same formalism, it is an error between the actual perception of the robot by the child (we can call it $\Phi[C,R]$) and the robot itself: $\Delta(\Phi[C,R]; M_R[R])$. Again, the robot does not have access to $\Phi[C,R]$, but it approximates it with $M_R[C,R]$. Finally we define the **child's perception error** at time t by $\Delta(M_R^t[C,R]; M_R^t[R])$. This error is taken in account only if the robot has a correct model of itself perceived by the child (only if $M_R[C,R]$ produce small prediction errors). Since this error assume that models built by the robot are correct, it is not used to update these models. It correspond to an error of the child: in order to repair it, the robot must explain the misunderstanding to the child or exaggerate an action to make sure it will be understood.

As an example, in the CoWriter activity, the child teach handwriting to the robot. The robot pretends to be a beginner, but it has its idea of a good handwriting. The robot is perfectly aware of its played progresses. But we want the child to be aware of the progress of the robot. In that perspective, the child's perception error corresponds to the sentence "*I make progress but the child think I don't*", while the prediction error of $M_R[C,R]$ corresponds to "*The child think I don't make progress, but maybe he think I do and I haven't understood him*".

III. STRUCTURE AND DYNAMIC OF THE MODELS

Each model contains the knowledge and possible actions of an agent. The dynamic between actions and knowledges must be encoded. Some causality can be assumed in advance (if the child gives a good feedback to the robot, it means that the robot-perceived-by-the-child makes progresses) while other can be learnt (e.g. if each time the robot looks at the head of the child the child stops to write). Each modelled

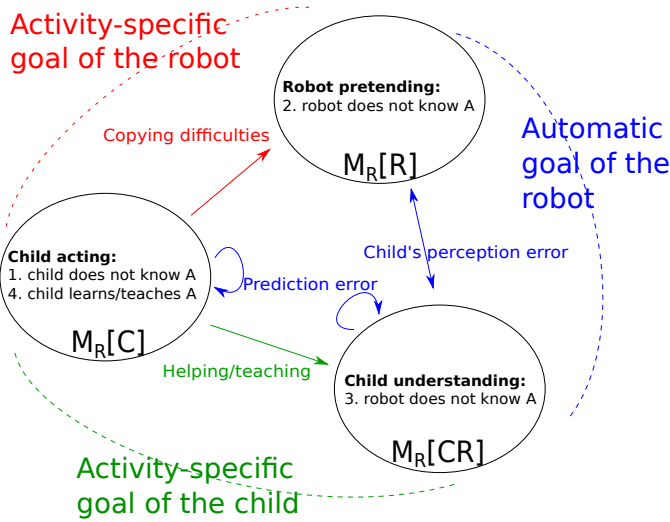


Fig. 1.

agent has its own goals, encoded as a reinforcement learning process. As an example, in CoWriter the robot-perceived-by-the-child ($M_R[C,R]$) is a learner and has the simple goal to make progresses. The child ($M_R[C]$) is modelled as a teacher and is assumed to have the goal to improve the robot's writing. Then, the goal of the robot ($M_R[R]$) is to keep a mutual understanding: its knowledges and actions must correspond to itself perceived by the child, and it must be able to predict the behaviour of the child. The schema on Figure 1 visually summarizes this example.

The goals of $M_R[C]$ and $M_R[C,R]$ depend on the activity and must be programmed each time we move to a new activity. They can be improved to better fit the child's behaviour by learning from experience. Contrariwise, the goal of $M_R[R]$ to keep a mutual understanding is independent and must be automatic.

REFERENCES

- [1] C. Breazeal, M. Berlin, A. Brooks, J. Gray, and A. Thomaz, "Using perspective taking to learn from ambiguous demonstrations," *Robotics and Autonomous Systems*, pp. 385–393, 2006.
- [2] H. H. Clark and S. E. Brennan, "Grounding in communication," *Perspectives on socially shared cognition*, vol. 13, no. 1991, pp. 127–149, 1991.
- [3] S. Suzuki, R. Adachi, S. Dunne, P. Bossaerts, and J. P. O'Doherty, "Neural mechanisms underlying human consensus decision-making," *Neuron*, vol. 86, no. 2, pp. 591–602, 2015.
- [4] K. Haroush and Z. M. Williams, "Neuronal prediction of opponents behavior during cooperative social interchange in primates," *Cell*, vol. 160, no. 6, pp. 1233–1245, 2015.