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Mutual Modelling in Educational Child-Robot Interaction

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Mutual Modelling in Educational Child-Robot Interaction

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Abstract

In any constructive social interaction, agents must be able to understand each other. This mutual understanding requires the ability to establish a mental model of the other, called mutual modelling. My *Ph.D.* is focused on mutual modelling in robotics: How robots can model other agents within social activities? Such models must be dynamic in order to keep track of shared knowledge, and adaptive in order to deal with specific behaviours of agents. This work is directly applied to the CoWriter Project, that aims at exploring how a robot can help children with the acquisition of handwriting [1]. Does mutual modelling in robots would actually improve educative Human-Robot Interactions?

1   Introduction

1.1   Mutual Modelling in HRI

As human individuals, most of our skills and knowledge have been built through social interactions. At the beginning we learn from parents language and basics of etiquette. Older, we learn culture and science mainly at school with teachers. To make possible such a social learning, both learners and teachers need to model each other: a teacher has to be aware of understood knowledge of his student, and a learner has to take the perspective of his teacher to understand his lessons.

Developed by Baron-Cohen and Leslie [1], the Theory of Mind (ToM) describes the ability to attribute mental states and knowledge to others. In interaction, humans are permanently collecting and analysing huge quantity of information to stay aware of emotions, goals and understandings of their fellows. In this work, we focus on a generalization of this notion: Mutual Modelling characterizes the effort of one agent to model the mental state of another one [5].

Until now, the work conduced by the Human-Robot Interaction (HRI) community to develop mutual modelling abilities in robots was limited to a first level of modelling (see Related Work section 2). Higher levels require the ability to

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[1]http://chili.epfl.ch/cowriter

recursively attribute a theory of mind to other agent (*I think that you think that ...*) and their application to HRI remains unexplored. Our research question is: *does a second level of modelling enables higher quality interactions?* We will operationalize this questions and the measures of quality in this document.

1.2 Application to the CoWriter project

Children facing difficulties in handwriting integration are more exposed to troubles during the acquisition of other disciplines as they grow up [3]. The CoWriter activity introduces a new approach to help those children [10]. Based on *learning by teaching* paradigm, it aims to repair self-confidence and motivation of the child rather than his handwriting performance alone.

Learning by teaching is a technique that engages students to conduct the activity in the role of the teachers in order to support their learning process. This paradigm is known to produce motivational, meta-cognitive and educational benefits in a range of disciplines [15]. The CoWriter project is the first application of learning by teaching approach to handwriting.

The effectiveness of our learning by teaching activity is built on the "protégé effect": the teacher feels responsible for his student, commits to the student's success and possibly experiences student's failure as his own failure to teach. The main idea is to promote in the child an extrinsic motivation to write letters (he will do it in order to help his "protégé" robot) and to reinforce the self-esteem of the child (he plays the teacher and the robot actually progress).

Our project requires a robot that play the role of a realistic learner to attract and challenge the child. At the moment, we have already implemented and tested the activity without mutual modelling ability in the robot [10]: the movements, the learning curve and the sentences of the robot are set beforehand and do not depend on the interaction. However, the realism of the learning robot and the protégé effect could be strongly improved if the robot was able to play his role according to a model of the child and, at a deeper level, to a model of *the robot-perceived-by-the-child* and *the child-perceived-by-himself*.

With a mutual modelling architecture, the robot could adapt his learning speed based on these models to make sure the child perceive its progresses. Furthermore, we want a robot that implicitly leads the child to correct himself while correcting the robot: for example, it could detect and exaggerate the mistakes of the child. At another scale, the robot could have a physical behaviour adapted to the child: *micro-behaviours* (gestures, gazes and sounds) must be based on the content of the interaction and on the behaviour of the child in order to improve the realism of the robot, to induce strong protégé effect and to make the interaction with the robot more comfortable for a young child.

In this thesis, we aim to construct a general framework for mutual modelling and, in the same time, to develop and test it through this activity. We have designed an experimental framework that enable long-term studies in real pedagogic/therapeutic contexts [11]. Following this work, our results will be based on experimental studies with children that face actual difficulties in learning handwriting.

2 Related work

In several contexts, a large amount of fields have introduced their own framework to describe mutual modelling ability [13]. In Developmental psychology, Flavell [7] denotes two different levels of perspective taking: The *cognitive connection* (I see, I hear, I want, I like...) and *mental representation* (what other agents feel, hear, want...). A specific deficit, namely autistic spectrum disorder, is accompanied by a lake of theory of mind in affected children. The study of this disorder led psychologists to develop false-belief experiments[1][8] that are used to bring out different levels of ToM in children.

In Psycholinguistics and collaborative learning, and more precisely in *computer supported collaborative learning* (CSCL), Roschelle and Teasley [17] suggested that collaborative learning requires a process of constructing and maintaining a *shared understanding* of the task at hand. The term "mutual modelling" was introduced in this context, and focused on knowledge states of agents [5]. Dillenbourg developed in [18] a computational framework to represent mutual modelling situations. He introduced the notation $\mathbf{M(A,B,X)}$ to denote "$\mathbf{A}$ knows that $\mathbf{B}$ knows $\mathbf{X}$".

Epistemic logic uses another notation to describe this concept: $\mathbf{K_A K_B X}$ where $\mathbf{K_i X}$ stands for "agent $\mathbf{i}$ knows $\mathbf{X}$. This notation is extended in order to describe more complex situations, like the *shared-knowledge* (all the agents of a group know $\mathbf{X}$) and the *common-knowledge* (all the agents of a group know $\mathbf{X}$, and know that all the agent know $\mathbf{X}$, and know that all the agents know that all the agents know $\mathbf{X}$..., etc.) [9].

However, HRI research has not, until now, explored the whole potential of mutual modelling. In [19], Scassellati gave an initial account of Leslie's and Baron-Cohen's theory of mind from the perspective of robotics. He limited his work to perceptual precursors (face detection or colour saliency detection). Since then, some work (including Breazeal [2], Trafton [21], Ros [16] and Lemaignan [12]) has been conduced to implement Flavell's first level of perspective taking [6] ("*I see (you do not see the book)*"), ability that is limited to the process of visual perception. In [14], Lemaignan implemented a system that compute in real-time the visual field of agents and estimate which objects are looked at. This time, the robot is not just aware of what *can be seen* by agents, but it perceives what *is currently looked*. Lemaignan used this system to measure Sharma's *with-me-ness* [20] (the visual commitment based on the expected focus of attention in an activity). He applied it to the CoWriter activity, as the number of times the child looks what he is expected to look according to the current task/event. His results provided by the algorithm were significantly close to human's perception of the *with-me-ness*. In this thesis, we aim to collect a quantity of such measures in order to infer information about second-order mutual models. Given this information, we will study how it can be used in order to improve the interactions.
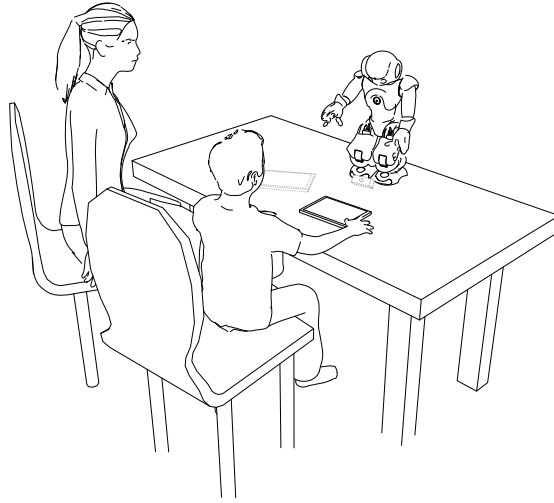
Figure 1: Our experimental setup: face-to-face interaction with a NAO robot. The robot writes on the tactile tablet, the child then corrects the robot by directly over-writing its letters on the tablet with a stylus. An adult (either a therapist or an experimenter, depending on the studies), remains next to the child to guide the work (prompting, turn taking, etc.). For some studies, a second tablet and an additional camera (lightened) are employed.

3 CoWriter: description of the activity

3.1 Interaction overview

Figure 1 illustrates our general experimental setup: a face-to-face child-robot interaction with an (autonomous) Aldebaran's NAO robot.

A tactile tablet (with a custom application) is used by both the robot and the child to write: in each turn, the child requests the robot to write something (a single letter, a number or a full word), and pushes the tablet towards the robot, the robot writes on the tablet by gesturing the writing (but without actually physically touching the tablet). The child then pulls back the tablet, corrects the robot's attempt by writing himself on top or next to the robot's writing, and "sends" his demonstration to the robot by pressing a small button on the tablet. The robot learns from this demonstration and tries again.

In [11], we added buttons to the tablet interface to allow the child to evaluate the robot. Even if this feedback does not necessarily concerns the progress of the robot's writing (children also use them to express how they like the robot), we can still exploit and improve this idea to get effective information about the child's perception of the robot.

The robotic implementation of this activity is explained in [10]. We used ROS to ensure the synchronization and communication between different devices. Likewise, the cognitive architecture for mutual modelling will be deigned as a ROS module that will collect information about the mental state of agents (here, the child, or *the robot-perceived-by-the-child*, or *the child perceived by himself*) in order to update its model of these agents. Then, other modules (for example the module that governs the learning algorithm of the robot) will use

these models to make decisions. We will better explain this design below, in section [cognitive architecture / implementation].

3.2 Generating and learning letters

Since our approach is based on teaching a robot to write, generating (initially bad) letters and learning from demonstrations is a core aspect of the project. The initial state of the robot and his ability to obviously learn from demonstrations of the child is the key to lend credibility to the activity and to induce the "protégé" effect.

The technical idea is simple: allographs of letters are encoded as a sequence of 70 points in 2D-space and can be seen as vectors with 140 elements $(x_1, ..., x_{70}, y_1, ..., y_{70})$. We arbitrary chose a set of allograph that define the initial state of generated letters. After the child provided a demonstration of a letter, the algorithm generates a new letter corresponding to the middle point between the last state and the demonstration. Details of this algorithm are presented in [10] and [11].

However, to keep the child engaged, the robot must learn at the right rate, not too fast otherwise the kid will have no opportunity for improving his skills and not too slow otherwise he may lose trust in his ability to improve the robot' skills. And a learning curve just based on the middle point between last state and demonstration will be too fast for one child, and too slow for another one. We need to make the robot aware of the child's perception of it progresses to take decision about its own learning curve. This awareness should be taken in account in our mutual modelling implementation, described below.

4 Framework for mutual modelling in robotics

4.1 Definitions

In this work, we extend the definition of mutual modelling from the representation of knowledge states to more global agent's states including knowledge but also positions, behaviours, emotions, beliefs, desires, pretending etc.

In order to enable second-order theory of mind (the ability to attribute a theory of mind to other agents), we define two order of agents: the *first-order-agents* concerns direct representations of agents by the robot (for example the child), while the *second-order-agents* concerns the representation of agents by agents (for example the robot-perceived-by-the-child). To model second-order-agent like the robot-perceived-by-the-child is crucial if we want to play with the perception of the robot, e.g. to make sure the child understand that the robot is learning from his demonstrations. We can as well define n^{th}-order agents to play with higher level of theory of mind. But taking into account high levels of mutual modelling requires hight complexity of calculation. In our implementation applied to the CoWriter activity, we will just use the first two orders that seem sufficient to bring out possible improvements of the interaction. Unlike the epistemic logic, our framework will not take into account infinite regress [4] of mutual modelling.

The sensitive devices (for example cameras, micros, robot's sensors ... and in the case of CoWriter the tablet's inputs) are used to measure a quantity of

perceived variables (the position in space of agents, the gaze targets, quality of demonstrations, the time to respond, the evaluation of the robot by the child...). Each *perceived variable* is associated with the model of one agent (in CoWriter, the positions in space of the child is associated with the model of the child, while the evaluation of the robot is associated with the model of the robot-perceived-by-the-child).

Some variables can't be directly measured by the sensitive devices and are deduced from other variables of models (see an example in the section [expected causality]). We call them *abstract variables.*

A model of an agent is the set of all the values of the perceived or abstract variables associated to this model. Since the values of variables are likely to change with the time, the models are dynamic.

4.2   Notations

The notation introduced by Dillenbourg in [18] is effective to describe complex multi-agent situations, but becomes quickly heavy when it is used for second-order mutual models: if $\mathbf{C}$ stands for the child and $\mathbf{R}$ for the robot, the model of the robot's level of writing ($\mathbf{LoW}$) as perceived-by-the-child would be written $\mathbf{M}(\mathbf{R}; \mathbf{C}; \mathbf{M}(\mathbf{C}; \mathbf{R}; \mathbf{LoW}))$.

In a context of HRI, most of the time we will consider one robot modelling human agent(s). Hence, we can assume that all the mutual models are processed by the robot. We will denote $\mathbf{M_A}$ the model of an agent $\mathbf{A}$, and $\mathbf{M_{A,B}}$ the model of the agent-$\mathbf{B}$-perceived-by-the-agent-$\mathbf{A}$. With this notation, the model of the robot-perceived-by-the-child is described by $\mathbf{M_{C,R}}$. In the rare cases of the usage of more than one robot, the model processed by different robots can be distinguished by an additive index ($\mathbf{Mi_A}$ describing the model of the agent $\mathbf{A}$ by the robot $\mathbf{i}$). Models of third and higher orders agent are noted as well with a sequence of agent: $\mathbf{M_{A,B,C,D}}$ stands for "*the model of* (($\mathbf{D}$ *perceived by* $\mathbf{C}$) *perc. by* $\mathbf{B}$) *perc. by* $\mathbf{A}$".

If x^t represents the value of a (perceived or abstract) variable X at time t, We can see the model of an agent $\mathbf{A}$ as a mapping $\mathbf{M_A^t} : X \mapsto x^t$ that provides the value of the associated variables. We note $\mathbf{M_A^t}(X) = x^t$.

4.3   Expected causalities

In order to deduce the values of abstract variables (that can't be obtained from direct perception), We can build a Bayesian model based on the knowledge from perceived variables. This model would contain the probabilities that abstract variables take values given the values of perceived variables. For example, if X is a boolean variable associated with the model $M_{\mathbf{C,R}}$ standing for "*the robot makes progress*" (abstract variable) and Y is a perceived variable also associated with the model $M_{\mathbf{C,R}}$ that represents a feedback given by the child via the button on the tablet (perceived variable), we would expect:

$$\mathbb{P}\left[\mathbf{M_{C,R}^t}(X) \; \middle| \; \mathbf{M_{C,R}^t}(Y) > 0\right] \sim 1$$

What means the probability that the child belief that the robot made progress is high given the fact he gave a positive feedback.

Some abstract variables can also depend on the dynamic of the perceived variables. A simple example is the following: if the robot shows an object and detects that the child saw it is pointing the object, then we expect that the child will gaze the target object. Let X be a boolean variable associated with $M_{\mathbf{C}}$ representing the truth value of "*the child understand the movement of pointing*" and Y be the variable also associated with $M_{\mathbf{C}}$ that stands for what the child is looking. Y can be measured from sensitive devices [14], but X must be deduced from the dynamic behaviour of the child. If the child looks at the hand of the robot but does not look at the target object in the following θ instants, the probability that the child understood the pointing movement becomes small:

$$\mathbb{P}\left[\mathbf{M}_{\mathbf{C}}^{t_0}(X) \,\middle|\, \mathbf{M}_{\mathbf{C}}^{t_0}(Y) = \textit{"robot's hand"} \bigcap_{t_1 > t_0}^{t_0 + \theta} \mathbf{M}_{\mathbf{C}}^{t_1}(Y) \neq \textit{"target object"}\right] \sim 0$$

Then, the robot and can make the decision to exaggerate its movement of pointing.

5 Cognitive architecture

5.1 Global description

Our cognitive architecture for mutual modelling can be designed in three main parts. A **perception part** will regroup all the modules that measure the values of the perceived variables using sensitive devices (camera, sensors, micros...). An example of module of the sensitive part could be the system developed by Lemaignan [14] that uses camera to measure a value of *with-me-ness*. These values are sent to the **mutual modelling part** that updates in real-time models with measured values of perceived variables and deducts the value of abstract variables. Finally, the **decision part** contains all the modules associated to the control of the robot (and other active devices like tablets in CoWriter). These modules can read values given by mutual models in order to compute decisions. In the example of the CoWriter activity, these modules are given by the system that learns and generate letters, but we can add a module that generates micro-behaviour, another that decides to switch to a new activity (e.g. drawing with the robot),... etc. The following subsections explain in detail the content and operation of the three parts of the architecture.

5.2 Perception modules

The sensitive modules contain all the module able to use sensitive devices to measure value of relevant perceived variables. Some of these modules are associated with the content of the interaction activity. In CoWriter, the learning module takes inputs of tablets to compute the new state of robot's writing. It defines a sensitive module, and the value of the new state of the robot to write a letter defines a perceived variable. As well, the evaluation of the robot by the child via the feedback buttons defines another perceived variable provided by the modules of the activity. Other modules are independent of the activity: the system that estimates the target objects looked by the child provides additive information not directly used by the modules of the activity.

5.3   Mutual modelling modules

Each perceived value measured by sensitive modules are associated with the model of an agent (or a nth-order agent). Each mutual model can be designed as a module that knows the list of its associated perceived variables and watch if the value of one of these variables has been changed. An additive module knows all the expected causalities and computes the values of abstract variables. Some expected causalities can be empirically learned and other set by hands.

5.4   Decision making

We believe that the values of variables provided by mutual modelling will provide rich and useful information for decision making. Taking in account these values to elaborate decision should improve the realism and the efficiency of the robot in the interaction. Just like the sensitive ones, the modules that take decision can be directly associated to the activity (in CoWriter, the choice of a new learning curve or the decision to suddenly make a big mistake), or can govern independent behaviour (for example a module that generate the micro-behaviour of the robot).

Some decisions, especially the one that will govern the micro-behaviours of the robot can be autonomously made by the robot. It will not strongly affect the content and objectives of the activity (in CoWriter the main objective is to provide the child with a new extrinsic motivation to write in helping the robot). But other decisions can have a high impact on the progress of the interaction: to stop an activity and to switch to a new one can frustrate a child that was committed into the activity. The conditions to make such a decision are not directly assessable, but must be learned by the robot. In order to make these decision cautiously, we propose to start by a Wizard-of-Oz approach and to move towards an autonomous approach following these steps:

1. **Wizard-of-Oz**: A human takes decisions; the robot learns

2. **Mixed-initiative**: The robot makes suggestions; a human agrees or disagrees

3. **Autonomous**: The robot makes decisions

The picture 2 visually summarize the global design of our architecture.

6   Implementation

6.1   ROS modules

The architecture will be implemented using ROS to synchronize the activity of different modules (written as ROS nodes). The perceived variables provided by sensitive modules and abstract variables provided by expected causalities will be published as messages on topics specific to the associated models. In the same way, modules of decision part will subscribe to the model's topic in order to watch the values of the variables that they need.
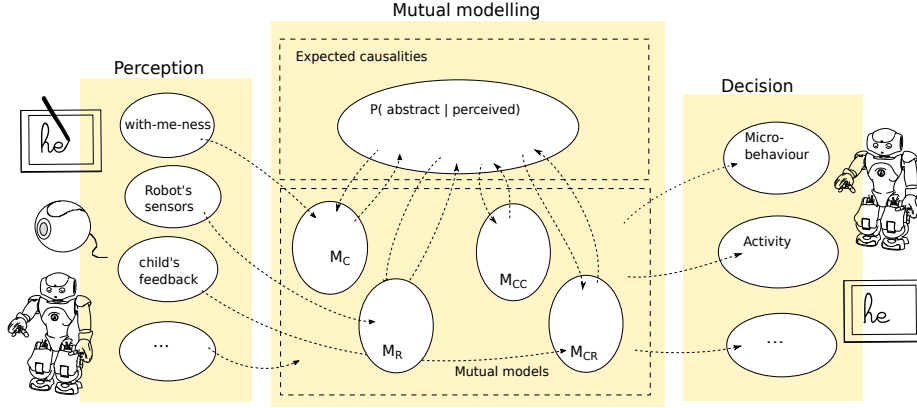
Figure 2: **Overview of the cognitive architecture**. Yellow squares represent different main parts. White ellipses represent modules. We named in example some content of modules and illustrated possible devices used for perception and decisions.

6.2 Integration to CoWriter

The CoWriter activity is already implemented using ROS. The main nodes that measure values of relevant variables are the robot's state machine, the node that governs the algorithm to learn/generate letters and the interpreter of the tablet inputs. Variables are already published on other topics used by the activity. We will additionally publish them on the topics associated to the mutual models.

We will use four models: the model of the robot $\mathbf{M_R}$, the model of the child $\mathbf{M_C}$, the model of the robot-perceived-by-the-child $\mathbf{M_{C,R}}$ and the model of the child-perceived-by-the-child $\mathbf{M_{C,C}}$.

Currently, the decisions made within the CoWriter activity that needs information from mutual models are the physical behaviour of the robot (for example, when the robot is waiting for a demonstration it looks the tablet) and the progress of the robot (the choice of the new state learned from the demonstration). We can add several decisions in order to improve the realism and the smoothness of the interaction (for example, the robot suddenly makes an exaggerated mistake, the robot changes its learning curve ...). If we want to take into account information from mutual modelling, we need to improve the algorithms of decision since we bring additive variables: for example, to change the learning curve will require some values of variables associated with $\mathbf{M_{C,R}}$ like the feedback of the child from tablet's buttons.

7 Evaluation

7.1 Hypothesis

The question of this thesis concerns the improvement of human-robot interactions brought by mutual modelling, especially in the educational context of the CoWriter activity. In order to evaluate this improvement, we hypothesize the following assertion:

Decisions made using additive information from second level of mutual modelling improve the quality of the CoWriter interaction.

To study this hypothesis, we need to rigorously define the *quality of the interaction.* Since the goal is to promote child's self-esteem and extrinsic motivation by inducing a "protégé" effect, we would like to measure the motivation of the child to play the activity and his satisfaction of the robot's progress.

7.2 Experimental studies

Such a measure can be defined by a large amount of variable that provide cues about the commitment of the child (quantity of demonstrations, time spend to write demonstrations, quality/progress of demonstration, progress of the robot, *with-me-ness* ...). The evaluation with feedback buttons can also be used to estimate how the child understands his role of teacher [11].

Along the successive steps to develop our mutual modelling architecture (each step being the addition of a new variable or a group of new variables to take into account), we will test the improvement of the interaction by measuring the above values. We will promote long-term studies with children facing real difficulties to learn handwriting with professional facilitators (teachers or therapists), following our previous works [11].

8 Conclusion and planning

We presented in this paper the research question of this thesis, which concerns the importance of mutual modelling in educative human-robot interactions. In order to study this question, we will develop an architecture based on mutual modelling that will collect information about mental and physical states of different agent. The stages of this construction will correspond to the successive additions of variables (or groups of variables) to take into account by the models. We will progressively extract pieces of response to our research question by testing our system each time a stage is crossed. We will use the framework for mutual modelling in HRI that we introduced in 4 in order to simplify notations and clarify the concepts.

During the first year of this thesis, our work was turned on the improvement and finishing of the CoWriter activity's implementation. We designed an experimental set-up that enable long-term studies in pedagogic/therapeutic contexts with children facing real difficulties to learn handwriting [11]. Finally, we started to implement additional sensitive modules independent of the CoWriter that will provide relevant variables to feed our future mutual modelling architecture (e.g. the system that estimates what the visual object of attention of the child [14]).

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