Child, Robot and Educational Material: A Triadic Interaction

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***Abstract*—The process in which a child and a robot work together to solve a learning task can be characterised as a triadic interaction. Interactions between the child and robot; the child and learning materials; and the robot and learning materials will each shape the perception and appreciation the child has of himself or herself, of the robot, and of the learning task. This paper discusses several experiments aimed at uncovering some of the dependencies inherent in this model of triadic interaction, and suggests steps towards developing more accurate measurement tools.**

I. Introduction

This research is conducted in the context of the EASEL[1] project, which focuses on educational child-robot interaction. In this context, my academic interest is how children learn through the use of smart technologies, and how these technologies can adapt to support a specific child's needs. This leads to a vision where child, robot and smart learning materials are engaged in a triadic interaction. For instance, this means that interactions between child and robot can shape how the child interacts with the learning materials, which in turn influences how the child learns [1].

In the educational domain, it is known that collaboration plays an important role in reaching one's optimal learning potential. According to Vygotsky [11], collaborating with a *more knowledgable other* allows a child to reach his or her "Zone of Proximal Development" (ZPD), where the child is able to acquire new cognitive skills or knowledge.

Much is already known about relationships between humans collaborating in pursuit of a common goal. Klein and Feltovich [7] look at *common ground* between teammates working on a joint activity. Common ground is defined as the shared mutual knowledge, beliefs and assumptions that evolve over the course of an interaction. A strong common ground leads to more efficient teamwork in terms of *interpredictability*. The willingness to be predictable, and to adapt one's behaviour, were found to be crucial in calibrating trust levels and building a symbiotic relationship [10], [8].

In order to understand the complete triadic relationship model, we need to gain insight into the mechanics of the three individual dyadic relationships: 1) Child interacting with robot; 2) Child interacting with learning materials; and 3) Robot interacting with learning materials. Firstly, for each of these interactions, given the educational context, we need to demonstrate which internal and external factors are likely to influence to the relationship. Secondly, we require tools for measuring the development of the various relationships over time.

[1]EASEL - Expressive Agents for Symbiotic Education and Learning: http://easel.upf.edu

II. Research

From the perspective of the second dyadic relationship (a child interacting with learning materials), we expect that the individual child's cognitive development is likely to be one of the factors influencing the way he or she interacts with the learning materials [11]. In order to effectively regulate the child's interaction with the learning materials, we would need to construct an appropriate model for the child's cognitive development within the task. We use an *inquiry learning* task as the primary mechanism around which the educational interaction takes place, as described by Klahr and Dunbar [5], [6]. A contextual analysis of such a task, in which two children collaborate without the aid of technology, showed that the developed inquiry task was suitable and that two coders could reliably recognise the inquiry processes. In a pilot study, we then developed a fully-automated prototype of an inquiry learning task, which allowed us to investigate and manipulate various scaffolding techniques, as well as to test how the required responsiveness and reliability of such an interactive system best supports a child's learning. Data about a child's performance during such a task, as well as his or her responses to the various scaffolds, will help construct a personalised model.

One method a learner can use to gain a deeper understanding of learning materials is to generate verbal explanations [2], [3], [4], [9]. In order to support a child in this process, we conducted an experiment in which a child was asked to verbally explain his or her various inquiry steps to a social partner. For details about the experiment setup, see [12]. In the context of our triadic interaction model, this experiment investigates which influence a manipulation in the first dyadic interaction (between child and robot) has on the second dyadic interaction (between child and learning material). Pilot results suggest that when a "less social partner" challenges a child to give a verbal explanation, there is a longer delay in response than when a child is challenged by a "more social partner" [12]. Qualitative analysis is currently ongoing, in which we focus on the *content* of their explanations.

We conducted an explorative pilot study, to more closely inspect how the social relationship between child and robot is shaped by their shared activities. Specifically, we investigated how a shared *extracurricular* activity can enrich this relationship. The robot and child would either engage in *only* a learning task, or would engage in a shared extracurricular activity (such as dancing or doing balancing exercises) *in addition* to a learning task. Results seem to indicate a difference between conditions in the child's perception of the robot. However, further analysis is needed to clarify both the nature and source of this difference, and identify possible implications this richer relationship will have for the child's and robot's interactions with the learning materials [2].

A common denominator in all these studies is related to finding suitable, objective measurement methods relevant for such young children. Since measuring the development of the social relationship between child and robot—and their attitude towards the robot and learning materials—is key to understanding the triadic model, we are constructing a collection of tools that can be used to guide semi-structured interviews. These tools are mostly based on various forms of associative picture-tasks, in which the child selects a picture from a certain collection and is asked to explain this choice. In addition, we often use more incidental metrics for specific experiments, such as response times and task performance.

III. Future directions

Since these measurements play such a key role in investigating the child-robot interaction, we plan to check the validity of the methods against observational data, after which they will be made available as a toolkit for similar research with this target group of young children. The main focus is on measurements involving: 1) the social relationship and bonding between child and robot; 2) the child's attitudes towards the robot and the task, and his or her perception of the robot and the task; and 3) the child's engagement with the robot and the task.

These methods will then be used in a long-term study to investigate the *development* of the relationship between the child and the robot over time, as well as the child's acquired knowledge. To do so, the robot will use performance metrics of the child's progress through the task to construct an internal model of the child's development, which will allow the system to tailor the task difficulty and scaffolding over repeated interactions. In addition to designing the robot behaviour models, one of the key challenges is to design an inquiry learning task that allows repeated and accurate collection of such performance metrics, and is flexible enough for long-term use on various personalised difficulty levels.

The third type of dyadic interaction, namely that between the robot and the learning materials, will likely influence the child's perception and expectations about the role of the robot, which will in turn influence the way the child interacts with the learning materials. For instance, at certain points in the learning task, a child will rely on the information he or she receives from the robot *about the task* (this could be a hint or an explanation, for example). We expect that the child has an initial *expectation* about the *value* of this information, which he or she will calibrate according to repeated positive or negative outcomes. This calibration process will be documented in a planned experiment, by tracking how often a child will update his or her answer to a question, after receiving a conflicting advice from a robot companion. For example, if the robot generally gives useful, relevant advice, the expectation is that the child will ascribe a high value to this input it receives from the robot. However, if the robot "malfunctions" and gives incomplete or wrong information, we expect this will result in a low ascribed value, causing the child to disregard the robot's advice and stick with his or her initial answer. We expect this process to be similar to the "trust calibration process" described by Simpson [10], and Lee and See [8].

[2]Davison, Schindler and Reidsma, submitted

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