Design challenges for long-term interaction with a robot in a science classroom

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Abstract— **This paper aims to present the main challenges that emerged during the process of the research design of a longitudinal study on child-robot interaction for science education and to discuss relevant suggestions in the context. The theoretical rationale is based on aspects of the theory of social constructivism and we use the collaborative inquiry as a framework to examine children's learning process who interact with a robotic learning companion. We identify two main challenges; (i) the development of robust on-demand systems for long-term interaction; and (ii) the design of developmentally appropriate scaffolding in embodied, semi-structured learning tasks. To address these challenges, we suggest (i) the development of a system for the detection of child's intention for interaction in the context of a classroom and (ii) the design of sensorized learning materials for the support of developmentally appropriate embodied learning experience.**

I. INTRODUCTION

Long-term interactions call for technical approaches that go beyond typical laboratory setups. When placing such a system in the wild for extended periods of time, it is required to function autonomously and respond to user-initiated, on-demand interactions. It should be robust enough to handle all interactions that fall within specific scenario contexts. Finding solutions for those technological challenges will allow the development of social robotic agents that are able to take into consideration contextual features as well as cognitive and socio-emotional characteristics of the interacting child. Consequently, social robots will be able to facilitate children's learning process in the complex environment of the classroom. With this vision, in this paper we present aspects of the research design of a long-term study on child-robot interaction in the context of the science lab of a school. More specifically, we describe the challenge of designing a robust on-demand system, and the challenge of measuring the state of the learning materials, and generating content and process scaffolds accordingly.

Previous research has indicated that the interaction with a humanoid robot may have an impact on children's learning. For example, a long-term empirical study has found that the interaction with a humanoid robot can have an impact on children's improvement of English language skills [1]. However, it was observed that children's learning increased only after a certain period of time (two weeks) of interaction with the robot (ibid.). Similarly, an effect of long-term interaction has been found on children's pro-social behaviour during their free play with a non-humanoid robot over the period of one school year [2]. In addition, research that focuses on children's activities with a social robot examines aspects of the social and emotional interaction between the child and the robotic companion. Examples include the investigation of empathetic behaviour of the robot [3] and the examination of the affective personalization of the robot in long-term child-robot interaction [4]. The investigation of physical interaction between a child and a robot in a learning setting has shown the robot was able to motivate the children to provide help by adapting its behaviour to the user [5].

In the proposed study, the robot, as a learning companion, scaffolds the child in order to follow a trajectory of inquiry learning process in the settings of science education. Children are going to work on an inquiry-learning task involving *physical* learning materials. The assignments provide the possibility for different difficulty levels and follow the structure of the inquiry learning cycle (preparation, hypothesis generation, experimentation, observation and concluding) [6]. The following sections present an overview of the challenges related to developing such a robust automated system for long-term interaction. We then present possible approaches specific to our physical inquiry learning scenario, and discuss how these can be used to provide scaffolding in a long-term educational context.

II. COLLABORATIVE INQUIRY

Learning is a dynamic process that evolves over long periods of time and allows the enhancement of children's cognitive structures by building upon the existing knowledge possessed by the learner [7]. In our research, we recognize that learning is a process that happens continuously during childhood in formal or informal settings; however, in the context of this paper we consider learning as an explicit process, which is connected to the child's cognitive and socio-emotional development and takes place when the child interacts with especially designed learning material together with an agent who has the role of the learning companion in this case the robot for a long period of time.

According to the proponents of the socio-cultural theory, this development takes different forms when a learning companion is present and intervene the process [8]. The

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Inquiry level	Question	Procedure	Solution
Confirmation Verify a concept in question with given procedure, outcome is known in advance	x	x	x
Structured inquiry Investigation of a given problem with a fixed method but unknown outcome	x	x	
Guided inquiry A question is presented to the learner without providing a method or the outcome	x		
Open inquiry Learner picks the problem to investigate as well as the method			

TABLE I

FOUR TYPES OF INQUIRY, RANGING FROM GUIDED/DEPENDENT TO OPEN/INDEPENDENT. DEPENDING ON THE TYPE, THE CHILD IS PRESENTED WITH A PREDEFINED QUESTION, A PROCEDURE TO INVESTIGATE THIS, AND THE CORRECT ANSWER.

learning companion can scaffold the learner to enter his or her Zone of Proximal Development (ZPD). However, simultaneously, children need the time and the space for experimentation and personal inquiry, which has led educational paradigms towards indirect interventions, one of which is the collaborative inquiry. The inquiry process [6], which is based on children's spontaneous curiosity for exploration and discovery of the phenomena that occur in the surrounding world as well as the process of the scientific thinking through which the explanation and understanding of those phenomena may emerge, provide a structured framework upon which children's cognitive and meta-cognitive skills can be built.

III. AIMS OF THE STUDY

Although these fundamental theoretical aspects have inspired previous research on child-robot interaction in learning settings [9], existing work provides limited information on the ways that learning process unfolds in long-term child-robot interaction. Long-term interaction provides the setting for a gradual transfer of the responsibility from the robot to the child, in which the child masters his or her independency through the four types of inquiry (confirmation, structured, guided and open inquiry, as described in table I). Ultimately, it is expected that the child will be able to transfer the knowledge of the inquiry process to a different setting. Consequently, this study will examine:

- The impact of a social robot on children's learning process in reference to the inquiry stages in a long-term interaction;
- The degree of children's achieved independency of inquiry process; and
- The transfer of knowledge of the inquiry process to a different learning setting.

IV. CHALLENGES

In our context of educational child-robot interaction, we identify two main challenges: 1) designing a robust on-demand system; and 2) providing adequate scaffolding in embodied, semi-structured learning tasks.

Both challenges are related to different aspects of sensing the world. We argue that a system must provide mechanisms for dealing with both aspects, if it aims to support an effective long-term interaction.

A. Robust on-demand systems

A key feature for supporting robust, on-demand interactions is the support of user-initiated interactions. The robot should be ready, at any time, to start a new interaction if any user wishes to do so. In the case of long-term sessions, this might be a repeated interaction with the same user, or it might be a new user interacting with the robot for the first time. This requires the system to store profiling details about individual users, as well as offer a user-friendly mechanism for initiating or ending an interaction.

A second important aspect is related to detecting and dealing with uncontrollable outside influences. Unlike in our typical lab setups, a long-term experiment will often take place in a public setting. Especially when involving children, it will often be the case that outside distractions influence the attention of the child and their focus on the interaction. An example could be other children, parents or teachers interrupting the session. In order to deal with such situations, the robot must have a way to estimate the state of the world *outside* the context of the scenario.

B. Scaffolding in embodied learning tasks

In our educational scenario children use inquiry techniques and embodied learning materials to investigate a topic of interest. A challenge is to keep the children engaged in this topic over longer periods of time. The learning system should be capable of offering a variety of tasks, ranging from a guided to an open inquiry style, while adapting the difficulty to an individual's personal level of cognitive development.

Using embodied learning materials presents an additional challenge over digital alternatives. To accurately follow a child's learning process through interactions with the materials, a robot must use external, dedicated sensors to detect the state of the learning materials. These sensors must be unobtrusive, but offer reliable readings in all real-world conditions. Once sensor output has been filtered, interpreted, and a high-level estimation of task progress has been made, the robot must be able to make an informed decision about suitable scaffolding.

V. APPROACH

The challenges stated above can be approached in several ways. In the following sections we present an approach adopted in the EASEL project, specifically aimed at facilitating one-on-one, long-term child-robot interactions with embodied inquiry-learning materials. For an overview of the EASEL integrated system architecture, please refer to [10]. This section focuses on the core modules related to sensing and tracking during a single session and over long-term repeated sessions.

A. Detecting intent to interact

Similar to the approach of Kanda et al. [1], we propose the use of personal RFID badges to identify an individual child. When initiating the on-on-one interaction, the child will scan their personal ID badge as soon as he or she approaches the robot. This supports very simple but robust, user-initiated interactions. Alternative technologies such as facial identification offer a more natural interaction, but often require more controlled (lighting) conditions and a pre-trained database of facial features.

While a child is engaged in the interaction, the system constantly stores and updates information about the child's progress through the learning task. For example, it stores correct and incorrect answers, which can be used to adapt the difficulty of the learning task. This persistent information is coupled to the child's unique RFID identifier, so that it can be loaded on a subsequent session, allowing the system to continue with the personalized interaction.

In addition to RFID tags, we use advanced Scene Analyser software [11] to detect nearby faces and sounds, and record features such as gaze direction and facial expressions. For future setups we are looking at possibilities for multi-party interactions, using this additional tracking information.

B. Sensorized learning materials

There is currently no generic, recommended solution for measuring the state of physical learning materials. Specific learning tasks will require unique, custom-built solutions.

A popular inquiry learning task uses a balance scale to investigate the physical properties related to torque [12], [13]. By placing weighted objects at various positions on a balance beam, children discover that both the weight of the object and it's distance to the pivot point influence the tilt of the balance. For this task, we explored several available sensor technologies to find an optimum combination of unobtrusive sensors that provide sufficient detection speed and reliability. We focused specifically on detecting the *tilt* of the scale, and detecting *which* uniquely colored objects were placed *where* on the balance.

By using embedded photoresistors we were able to accurately determine the location of objects on the balance. By using an external overhead camera we were then able to identify the unique color of the objects on those specific locations. The tilt of the balance beam was measured by a potentiometer in the central pivot. These cheap, simple and reliable sensors require almost no calibration and can function accurately in a wide range of environments.

A prototype (see fig. 1) of this setup was tested with 45 children (5-10 years old) during a period of 5 days, resulting in a total of 1700 instances in which the state of the learning materials was measured. This prototype test consisted of a series of controlled short-term interactions. The primary goal of this experiment was to determine sensor requirements and test sensor accuracy across varying conditions. Over all days, the combined sensor values were able to predict the complete state of the learning materials with an average reliability of 95%.

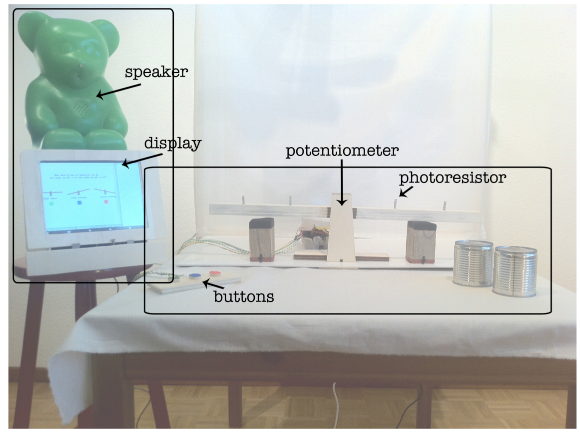

Fig. 1. Our prototype of a sensorized balance beam, showing the physical learning materials with embedded sensors and a basic feedback system.

Sensing and storing a child's progress through a task allows us to offer personalized difficulty levels and personalized scaffolding for subsequent tasks. For example, the system might detect several errors in assignments in which the *weight* of pots is manipulated. A following interaction with this child could focus specifically on investigating this aspect, while offering content scaffolding in the form of an intuitive example: "Imagine an elephant and a mouse sitting on either end of a seesaw. Which side would go down?".

VI. Designing a long-term interaction model

Given that the robot is now able to detect and identify individual users, and is able to reliably estimate the state of the learning materials, we propose a solution for generating appropriate content and process scaffolding.

Our interaction system is built around modular dialogue models. A dialogue model consists of rule-based templates, responsible for defining reactions to specific combinations of events and triggers [14]. Using a hierarchical dialogue model approach, we define various layers of interaction.

The most abstract dialogue model keeps track of the overall flow through an interaction. This typically starts at a *greeting* phase when a child scans their RFID badge, and ends with a *goodbye* phase when the child leaves, or when the assignment is completed. It contains references to a collection of subdialogues that can cope with more detailed interaction patterns, ranging from off-topic smalltalk to specific learning-tasks. As the interaction progresses, this approach allows for high-level termination, switching and jumping between subdialogues.

An example of a possible abstract, top-level dialogue model is shown in figure 2. This model contains references to more specific subdialogues, each of which consists of dialogue rules that are appropriate for that phase of the interaction. Together, these subdialogues describe a cohesive interaction pattern.

On lower levels of abstraction, we define these subdialogues to cope with specific inquiry learning situations. For example, the "Do task" subdialogue could contain the inquiry

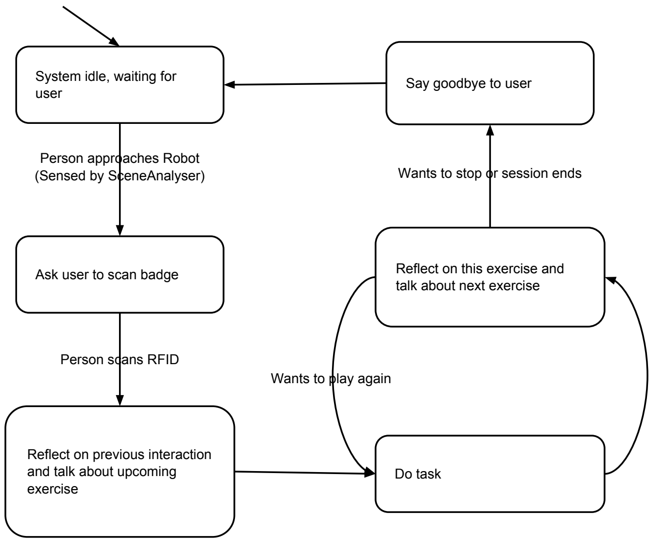

Fig. 2. An abstract, high-level dialogue model shows how various subdialogues work together to form a cohesive interaction.

process of *preparation*. This process requires the child to prepare the balance in a certain target state (i.e. place specific weights on the balance in predefined positions). By comparing the current sensed state of the learning materials to this target state, the robot is able to accurately measure correct and incorrect placements and provide appropriate scaffolding to the child. A more detailed in-depth description of these context-specific, low-level dialogue models is outside the scope of this paper.

Using this approach, we have defined a total of 22 relevant content and process scaffolds for each balance beam task. Based on the sensor data, all such scaffolds are triggered automatically with high reliability, while the child naturally progresses through the inquiry process.

VII. Conclusion

This study aims to contribute to the research agenda of the long-term child-robot interaction in learning settings from a process-oriented perspective, by examining the ways that social robots can help the children "learn how to learn". To design a long-term study that will allow learning processes to unfold, we need to overcome certain challenges. Firstly, we suggest the development of systems suitable to detect the intention for interaction in order to achieve robust on-demand systems for long-term interaction in the context of a classroom. Secondly, we propose the design and the development of sensorized learning materials. This approach allows the system (learning material) to communicate with the robot and at the same time to support children's embodied learning experience. Finally, we discuss our approach for designing hierarchical dialogue models, which are suitable for supporting automatic scaffolding for inquiry learning in the context of an ongoing multi-session interaction.

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