Adaptive Robot Second Language Tutoring for Children

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1 RATIONALE

Empirical evidence has demonstrated that learning with and from a physically present, interactive robot can be more effective than learning from classical on-screen media [6, 8]. In the L2TOR project we work on using the robot Nao to support *second language learning*, a problem that becomes increasingly important nowadays. We focus on preschool children in the age of 5-6yr, for whom it is crucial to develop adequate knowledge of the academic language as later educational success builds on it [4, 7].

To efficiently support learning, the robot's behavior during tutoring interactions must adapt to the learner. Recent research has shown that participants who received personalized lessons from a robot (based on heuristic skill assessment) outperformed others who received non-personalized training [8]. Furthermore, suboptimal robot behavior (e.g., too much, distracting, mismatching or in other ways inappropriate behavior) can even hamper learning [5].

The present PhD project focuses on *how a robot can adapt to an individual child to provide an engaging tutoring interaction that supports in learning a second language.* To allow for adaptation and personalization in the course of teaching lessons, it is of great importance to establish a knowledge base about the child including the following issues: (1) Tracing the child's knowledge state regarding the mastery of linguistic skills; (2) Tracing the child's affective state regarding the engagement in the interaction; (3) Collecting information about more persistent traits and abilities of the child, e.g., the child's perseverance or learning speed.

2 RESEARCH PROGRESS SO FAR

To achieve sub-goal (1), we implemented a model based on Bayesian Knowledge Tracing [2] and extended it with action decision nodes to allow the robot to use the traced information for predictive decision-making. This enables the system to adapt the choice and difficulty of each learning task based on the traced skill master of the child [9], with the goal to have the child work in the "zone of proximal development" [11]. To evaluate this approach, the adaptive system was compared with a randomized training in a version of the game "I spy with my little eye" [9]. In this game, one player describes one of the cards laying on a desk using words of the second language, and the other player has to guess which one it is. We ported this game to a tablet screen and let the robot play the part of the describer. The robot decides autonomously and in accord with the experimental condition on the set of cards presented (including distractor objects) as well as the 2nd language word used to refer to a property of the right object. The participant has to select the described object by tapping on it. The first evaluation has been done with adult participants who had to learn an artificial language. The learning gain was measured in terms of the correctness of participants' answers during the game, and with an additional post-test which asked for the learned words. Results show that participants playing with the adaptive system performed significantly better than in the randomized control condition.

Next, we tested the system with children of the target age group of 5-6yr and let them learn a few English words [3]. Children show a high degree of inter-individual variation and need child-specific adaptations of, for instance, the robot behavior and synthesized speech to enable them to understand what the robot says. Therefore, we modified the tablet game (pictures & buttons) and the robots' behavior (slower tts & movements & more explanations while using easier words) to be more suitable for children while the underlying game mechanics remained untouched. The results show that in both conditions the children learned second language vocabulary, however there is no significant difference in the post-test between the adaptive condition compared to the control group. This might have resulted from the short interaction duration of 20 minutes, or an unsuitable post-test to access the learning gain of children, which has to be further investigated in the future. However, we observed an impact of the adaptive system on children's engagement: children who played with the adaptive system were significantly more engaged at the end of the interaction than children in the control condition. Children's engagement was accessed by ratings of non-experts who watched video recordings of the interactions.

3 ONGOING WORK

Since an effect of our adaptive tutoring system on the engagement of preschool children was observable during training, we decided to further include *engagement* as a target variable into our decision-making model. Therefore, we have to reach our next sub-goal (2) of tracing the child's affective state during the tutoring interaction. For that purpose, we conducted expert interviews in kindergartens [10], asking preschool teachers to freely utter their impressions

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about children's cognitive and affective state while watching videos of child-robot tutoring interaction (from the previous study). These interviews were guided by the following questions: 1.) Do you think the child is engaged and attentive?; 2.) Based on which behavioral cues do you come to this appraisal?; 3.) What are possible actions for the robot to positively influence the engagement and attention? The results of a qualitative analysis of the expert interviews indicated that some behavioral cues were mentioned for most of the children by most of the experts (e.g., gazing away, sitting still). In addition, these cues are traceable by a Microsoft Kinect.

Given this information, we plan to implement a Naive Bayesian classifier to detect and trace the child's *interaction engagement* during the interaction. Because of probably noisy sensor data, we also plan to include more reliable cues such as the "response time" and the "task accuracy". The resulting engagement state will be included into our current approach and the action space will be extended to include actions to influence the child's engagement. In result, the system will be able to plan the next steps in the tutoring interaction not only based on the current knowledge state of the child, but also based on the interaction engagement level. To get an idea how the actions reported during the expert interviews influence the child's knowledge and affective state, and to find additional actions to be added, we plan to develop a teaching approach together with pedagogical experts that is suitable for a humanoid robot like Nao. The approach will be based on existing learning/teaching theories from human-human interaction, and will inform the predictive decision-making process itself. Afterwards, the system will be capable of simulating action effects and to decide whether to continue with teaching or if the engagement has to be raised first to allow for efficient teaching (i.e., a low interaction engagement might result in a low learning gain and higher probability to give a wrong answer). The system will be evaluated in a study comparing the adaptation based on affect- and knowledge-state with the adaptive system from study (1) as the control condition. Again, the participants will be preschool children in the age of 5-6yr, but the previously used tablet game will be modified. Since the "I spy with my little eye" was very repetitive and therefore not very engaging itself, we plan to develop another game which will include more various tasks, e.g., moving objects or repeating the target words. To assess the learning gain of the children, we plan to use and pretest a modified version of the previously used post-test.

4 FUTURE WORK

Future steps will aim at reaching sub-goal (3), for which we plan to store all interaction data for a child, including the given answers, response times etc., together with the affective and knowledge states in discrete intervals. By using this long-term history, the system will be capable of inferring further information, e.g., is the child a slow or a fast learner, and adapt its behavior accordingly. To evaluate long-term effects of the system, we will conduct a study with 5-6 learning session over 2 weeks in kindergartens to see how engagement and learning gain evolve over time. Therefore, the previously used tablet game will be extended along an engaging and entertaining story line. For the control-condition, the short-term adaptive system from (2), including affect and knowledge tracing, will be used.

During our initial experiments we recognized that some participants in the adaptive condition found the system a bit "eerie", because it spotted and retaught the words they struggled with until they learned them. To overcome this issue, the system's decisions should be made more transparent by means of verbal explanations, e.g., Robot: "Last time we struggled with learning this word. Let's try it again together!". This might also motivate the child to exert oneself, let the system appear to memorize all the joint learning experiences and help to establish a common history. These aspects might further lead to a greater acceptance of the robot as a learning partner and an increased intrinsic motivation of the child to interact again. This could be especially effective for children of such a young age, because for them even inanimate objects as a robot or a teddy-bear still possess a "soul". Additionally, [1] showed that children younger than 12 years believe that a robot possessed several human attributes and assign cognitive beliefs to it by stating that it would remember them and knew their feelings. We thus hypothesize that a system, that verbalizes its knowledge and decisions outperforms a system without verbalization. This will be tested in the future.

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