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A new biomimetic approach towards educational robotics: the Distributed Adaptive Control of a Synthetic Tutor Assistant

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Abstract. Many fields can profit from the introduction of robots, including that of education. In this paper, our main focus is the advancement of the Synthetic Tutor Assistant (STA), a robot that will act as a peer for knowledge transfer. We propose a theory of a tutoring robotic application that is based on the Distributed Adaptive Control (DAC) theory: a layered architecture that serves as the framework of the proposed application. We describe the main components of the STA and we evaluate the implementation within an educational scenario.

1 INTRODUCTION

Robots are now able to interact with humans in various conditions and situations. Lately, there has been an increased attempt to develop socially interactive robots, that is, robots with the ability to display social characteristics: use natural communicative cues (such as gestures or gaze), express emotional states or even establish social relationships, all of which are important when a peer-to-peer interaction takes place [20]. In fact, given the current technological advancements, we are now able to develop robotic systems that are able to deal with both physical and social environments. One of the greatest challenges in the design of social robots is to correctly identify all those various factors that affect social interaction and act in accordance [43]. Indeed, different studies have shown that the complexity in the behavior of robots affect how humans interact with robots and perceive them [30, 55, 7, 52].

There are many fields that can profit from the introduction of robots [13], they include health care [9], entertainment [18], social partners [8] or education [21, 41]. Here we focus on the latter, by advancing the notion of the Synthetic Tutor Assistant (STA) (see section 3) which is pursued in the European project entitled Expressive Agents for Symbiotic Education and Learning (EASEL). In this perspective, the robot STA will not act as the teacher, but rather as a peer of the learner to assist in knowledge acquisition. It has been shown that robots can both influence the performance of the learner [41] and their motivation to learn [29]. One of the main advantages of employing a robotic tutor is that it can provide assistance at the level of individual learners, given that the robot can have the ability to learn and adapt based on previous interactions.

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Through education, people acquire knowledge, develop skills and capabilities and consequently form values and habits. Although there exist several educational approaches that could be considered, here, we will focus on Constructivism [35]. Constructivism proposes an educational approach based on collaboration, learning through making, and technology-enhanced environments. Such approach aims at constructing social interaction between the participant and the STA as it implies a common goal for both learners-players [45].

We consider tutoring as the structured process in which knowledge and skills are transferred to an autonomous learner through a guided process based on the individual traits of the learner. Here we present an approach where both the user model and the STA are based on a neuroscientifically grounded cognitive architecture called Distributed Adaptive Control (DAC) [51, 47]. On one hand, DAC serves as the theory which defines the tutoring scenario: it allows us to derive a set of key principles that are general for all learning processes. On the other hand, it is the core for the implementation of the control architecture of the STA, the robotic application. Following the layered DAC architecture, we propose the STA that will deploy tutoring strategies of increasing levels of complexity depending on the performance and capabilities of the learner. The DAC theory serves as both the basis for the tutoring robotic application, user model as well as for the implementation of the STA. Such design guarantees a tight interplay between the robotic application, the user and their interaction.

The present study is organized as follows: first, we present the background theory of the tutoring robotic application, the DAC theory, and we describe the tutoring model applied. Furthermore, we introduce the key implementation features of the STA based on DAC. To assess the first implementation of our system, we devised a pilot study where the STA performs the role of a peer-teacher in an educational scenario. The proposed scenario consists of a pairing game where participants have to match an object to its corresponding category. The setup was tested with both children and adults. The game had three levels of increased difficulty. Questionnaires distributed after every interaction to the players were used to assess the STA's ability to transfer knowledge.

2 DAC COGNITIVE ARCHITECTURE AND LEARNING

To provide a model of perception, cognition and action for our system, we have implemented the DAC architecture. [51, 47]. DAC is a theory of mind and brain, and its implementation serves as a real-time neuronal model for perception, cognition and action (for a review see [49]). DAC will serve both as the basis for the tutoring model as well as the core of the implementation of the STA.

2.1 Distributed Adaptive Control (DAC)

Providing a real-time model for perception, cognition and action, DAC has been formulated in the context of classical and operant conditioning: learning paradigms for sensory-sensory, multi-scale sensorimotor learning and planning underlying any form of learning. According to DAC, the brain is a layered control architecture that is subdivided into functional segments sub-serving the processing of the states of the world, the self, interaction through action [48], and it is dominated by parallel and distributed control loops.

DAC proposes that in order to act upon the environment (or to realize the *How?* of survival) the brain has to answer four fundamental questions, continuously and in real-time: *Why, What, Where and When*, forming the H4W problem [50, 49]. However, in a world filled with agents, the H4W problem does not seem enough to ensure survival; an additional key question needs to be answered: *Who?*, which shifts the H4W towards a more complex problem, H5W [46, 39].

To answer the H5W problem, the DAC architecture comprises of four layers: Somatic, Reactive, Adaptive and Contextual, intersected by three columns: states of the world (exosensing), states of self (endosensing) and their interface in action (Figure 1). The Somatic Layer represents the body itself and the information acquired from sensations, needs and actions. The Reactive Layer comprises fast, predefined sensorimotor loops (reflexes) that are triggered by low complexity perceptions and are coupled to specific affective states of the agent. It supports the basic functionality of the Somatic Layer in terms of reflexive behavior and constitutes the main behavioral system based on the organism's physical needs. Behavior emerges from the satisfaction of homeostatic needs, which are also regulated by an integrative allostatic loop that sets the priorities and hierarchies of all the competitive homeostatic systems. Thus, behavior serves the reduction of needs [25] controlled by the allostatic controller [42].

The Adaptive Layer extends the sensorimotor loops of the Reactive Layer with acquired sensor and action states, allowing the agent to escape the predefined reflexes and employs mechanisms to deal with unpredictability through learning [14]. The Contextual Layer uses the state-space acquired by the Adaptive Layer to generate goal oriented behavioral plans and policies. This layer includes mechanisms for short, long-term and working memory, formating sequential representations of states of the environment and actions generated by the agent or its acquired sensorimotor contingencies. The DAC architecture has been validated through robotic implementations[19, 42], expanded to capture social interactions with robots [52, 39] as well as providing novel approaches towards rehabilitation [47]. Here, the implementation of DAC serves two main purposes. On the one hand, it acts as the grounding theory for the pedagogical model: it allows us to derive and deduce a set of key principles that are general for all learning processes. On the other hand, DAC is the core for the implementation of the STA.

2.2 Phases of learning

Based on the formal description of learning from the DAC architecture which has been shown to be Bayes optimal [48], we will focus on two main principles as it has a dual role within EASEL. On one hand, DAC is the core for the implementation of the Synthetic Tutor Assistant (STA). On the other hand, following the layered architecture, the STA deploys pedagogical strategies of increasing levels of complexity.

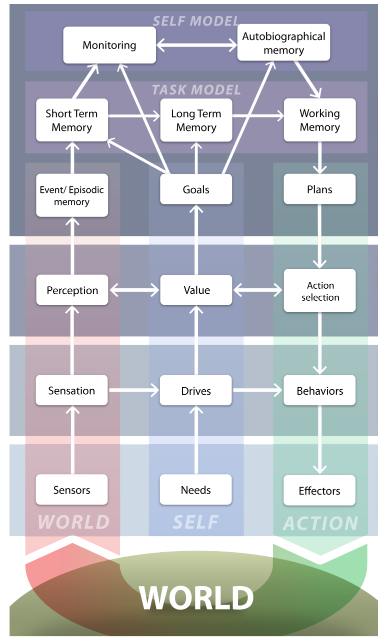

Figure 1. The DAC architecture and its four layers (somatic, reactive adaptive and contextual). Across the layers we can distinguish three functional columns of organization: world (exosensing), self (endosensing) and action (the interface to the world through action). The arrows show the flow of information. Image adapted from [49].

First, DAC predicts that learning is bootstrapped and organized along a hierarchy of complexity: the Reactive Layer allows for exploring the world and gaining experiences, based on which the Adaptive Layer learns the states of the world and their associations; only after these states are well consolidated, the Contextual Layer can extract consistent rules and regularities. We believe that the same hierarchy is applicable in the pedagogical context. Secondly, DAC predicts that in order to learn and consolidate new material, the learner undergoes a sequence of learning phases: resistance, confusion and resolution. *Resistance* is a mechanism that results from defending one's own (in)competence level against discrepancies encountered in sensor data. In DAC these discrepancies regulate both perceptual learning and the engagement of sequence memory. Consistent perceptual and behavioral errors lead to the second phase, namely *confusion*, the necessity to resolve the problem and learn through readapting. *Confusion* modulates learning as to facilitate the discovery and generation of new states to be assessed on their validity. In other words, to assist in performing abduction. Finally, *resolution* is the very process of stabilizing new knowledge that resolves the earlier encountered discrepancies and errors. This DAC-derived learning dynamics have been grounded in aspects of the physiology of the hippocampus [40] and pre-frontal cortex [32], and they reflect the core notions of Piaget's theory of cognitive development assimilation and accommodation through a process of equilibration [37, 56].

Human learners show a large variability in their performance and aptitude [16] requiring learning technologies to adjust to the skills and the progress of every individual. For learning to be efficient and applicable for as broad a range of students as possible, individual differences need to be taken into account. The critical condition that has to be satisfied, however, is that the *confusion* needs to be controllable so that it adjusts to the skills and the progress of individual students. This is consistent with the classical notion of Vygotsky's Zone of Proximal Development which is the level of knowledge that the learner can acquire with external assistance of a teacher or a peer [54]. Individualization thus serves the identification of this epistemic and motivational level.

Monitoring, controlling and adjusting the phase of confusion is what we call *shaping the landscape of success*. This approach is consistent to the notion of scaffolding, a technique based on helping the student to cross Vygotsky's Zone of Proximal Development. The concept of controlled confusion, as well as of individualized training, has already been tested in the context of neurorehabilitation using DAC based Rehabilitation Gaming System (RGS) which assists stroke patients in their functional recovery of motor deficits [10, 11]. RGS indeed effectively adjusts to individual users in terms of difficulty, allowing for an unsupervised deployment of individualized rehabilitation protocols.

Within the DAC architecture, the processes of learning are not isolated within single layers but they result as the interplay among them and the external world [51]. Although both the processes of learning deployed in the current experiment (resistance, confusion, resolution) and the layers of the DAC architecture (Reactive, Adaptive, Contextual) constitute a specific order and initial dependencies, their relation is not fixed. Depending on the learning goal (learning a new concept, contextualizing new information within a broader scale, etc.) the tutoring may be focusing on one of the three layers. In order to systematically traverse the three phases of learning distinguished here, the user is guided through a goal-based learning.

By incorporating DAC within the educational framework, our aim is to be able to create the feeling of resistance and confusion to introduce new knowledge specific for every individual student. Adjusting to the skills and the progress of individual students may result in keeping the process of acquisition motivating; so it is essential that despite helping the student to overcome certain difficulties, the task remains challenging enough.

3 THE SYNTHETIC TUTOR ASSISTANT (STA)

The STA emerges as the interplay of the three layers of DAC architecture. It is the STA that provides individualized content, adapted to the needs and capabilities of each student. Here we layout the framework for the implementation of the STA within the DAC architecture. The Reactive Layer provides the basic interaction between the student, tutor and teaching material through a self-regulation system and an allostatic control mechanism. It encompasses the basic reaction mechanisms guiding the student through the learning material in a predefined reactive manner and is based on a self-regulation mechanism that contains predefined reflexes that support behavior. Such reflexes are triggered by stimuli that can be either internal (self) or external (environment) and are coupled to specific affective states of the agent.

The Adaptive Layer will adjust the learning scenario to the needs and capabilities of the student based on the user model that is online updated throughout the analysis of the interaction. To do so, the STA needs to assess the state of the student (cognitive, physical, emotional), learn from previous interactions and adapt to each student. This knowledge will support the rich and multimodal interactions based on a the DAC control architecture. Finally, the Contextual Layer will monitor and adjust the learning strategy over long periods of time and over all participating students through Bayesian memory and sequence optimization. In the pilot experiment reported here, we are assessing the properties of the Reactive Layer of the STA in an educational scenario.

3.1 Behavioral modulation

In case of the STA, the main purpose of the self-regulating mechanism of the Reactive Layer is to provide the tutor with an initial set of behaviors that will initiate and maintain the interaction between the STA and the student. Grounded in biology, where living organisms are endowed with internal drives that trigger, maintain and direct behavior [25, 38], we argue that agents that are endowed with a motivational system show greater adaptability compared to simple reactive ones [2]. Drives are part of a homeostatic mechanism that aims at maintaining stability [12, 44], and various autonomous systems have used self-regulation mechanisms based on homeostatic regimes [6, 3].

Inspired by Maslow's hierarchy of needs [33], Hull's drive reduction theory [25] and tested in the autonomous interactive space Ada [15], the robots behavior is affected by its internal drives (for example the need to socialize - establish and maintain interaction). Each drive is controlled by a homeostatic mechanism. This mechanism classifies the drive in three main categories: *under*, *over* and *within* homeostasis. The main goal of the STA is to maximize its effectivity (or "happiness") as a tutor assistant, by maintaining its drives within specific homeostatic levels. To do so, the STA will need to take the appropriate actions. These states are focusing on the level of interaction with the learner and its consistency. Coherence at the behavioral level is achieved through an extra layer of control that reduces drives through behavioral changes, namely the allostatic control. Allostasis aims at maintaining stability through change [34]. The main goal of allostasis is the regulation of fundamental needs to ensure survival by orchestrating multiple homeostatic processes that directly or indirectly help to maintain stability.

The allostatic controller adds a number of new properties of the STA-DAC architecture, ensuring the attainment of consistency and balance in the satisfaction of the agent's drives and foundations for utilitarian emotions that drive communicative cues [53]. This approach strongly contradicts the paradigm of state machines standardly employed in comparable approaches and, in general, within the robotics community. State machines provide a series of closed-loop behaviours where each state triggers another state in function of its outcome. Here, drives are not associated on a one-to-one basis with a specific behavior. Instead, each behavior is associated with an intrinsic effect on the drives and with the usage of the allostatic controller, drives, and therefore behavior, change as the environment changes. With such design, drives modulate the robot's behavior adaptively in the function of every learner and the learning environment in general. Although in our current implementation, the mappings are hard-coded as reflexes (Reactive Layer), according to the DAC architecture, the mappings should be learnt through experience to provide adaptation.

3.2 The setup (software and hardware)

The DAC architecture and framework proposed are mostly hardware independent, as it can be applied in various robotic implementations [19, 42, 53, 31]. Here, the implementation aims at controlling the behavior of the robot and it involves a large set of sensors and effectors, designed to study Human-Robot Interaction (HRI). The setup (see figure 2) consists of the humanoid robot iCub (represented by the STA), the Reactable [23, 27] and a Kinect. The Reactable is a tabletop tangible display that was originally used as a musical instrument. It has a translucent top where objects and fingertips (cursors) are placed to control melody parameters. In our scenario, the usage of the Reactabe allows us to construct interactive games tailored to our needs. It furthermore provides information about the location of a virtual and physical object placed on the table and allows a precision that can hardly be matched using a vision based approach. In our lab, we have employed the Reactable in various interaction scenarios using the MTCF framework [28], such as musical DJ (cooperative game where the robot produces music with humans), Pong (competitive 2D simulated table tennis game) and Tic Tac Toe. The use and control of all these components allows the development of various interactive scenarios including educational games investigated here and allow the human and the robot to both act in a shared physical space. An extensive description of the overall system architecture can be found in [31, 52, 53]. The setup was designed to run autonomously in each trial, being the allostatic control the main component for providing the guidance for the learner/player during the task.

Figure 2. Experimental setup of the robot interacting with a human using the Reactable for the educational game scenario. In the image you can see the participant holding an object used to select an item from the Reactable (round table with projected images of countries and capitals). The participant is facing the iCub. The projected items are mirrored, so each side has the same objects.

4 TOWARDS ROBOTIC TEACHERS

In order to test the implementation of the STA-DAC as well as to evaluate the effectiveness of our scenario depending on different social features of the robot, we conducted a pilot study where the robot had the role of a tutor-peer.

The aim of the experiment focused on testing the effect of social cues (in this case, facial expression and eye contact) in HRI during an educational game. The goal was to test whether the variation of these social cues could affect the knowledge retrieval, subjective experience, and the very behavior towards the other player.

4.1 The educational scenario

The first question raised during the development of the STA is whether it can be an effective peer for the learner, both in terms of the social interactions and the impact on learning. Hence, the focus of this experiment is to study whether the modulation of certain behavioral parameters (based on the DAC architecture and the proposed behavioral modulation system), such as the use of eye contact and facial expressions, can change the acquisition of knowledge of a specific topic and the subjective experience of the user. On the one hand, eye contact can strengthen the interaction between the learner and the STA, for gazing can affect the knowledge transfer and the learning rate [36]. On the other hand, facial expressions can be used as a reinforcement of the participant's actions (the robot displays a happy face when the participant's choice is correct and a sad face when the matching is wrong), and could be considered as a reward.

The game-like scenario which we deployed is exercising Gagne's five learning categories [22]: verbal information, intellectual skill, cognitive strategy, motor skill and attitude. The game is based in a physical task, so the participants have to use their motor skills and, in order to solve the task, they have to develop a cognitive strategy to control their internal thinking processes. We also implemented three components of intellectual skill: concept learning, that is, learning about a topic; rule learning, used to learn the rules of the game; and, problem solving processes to decide how to match the pieces.

The educational scenario is a pairing game, where participants need to pair objects appearing on the Reactable to their corresponding categories. The pairing game is grounded in the premises of constructivism, where two or more peers learn together. Here the robot behaves similarly to a constructivist tutor: instead of just giving the information directly, it helps the student to understand the goal of the game (and, for example, reminding the subject the correct ways of playing) and it provides feedback regarding his actions (the robot only tells the correct answer to the subject when he has chosen a wrong answer, not before). For example, if the human selects a wrong pair, the robot indicates why the selection is wrong; it also comments on the correct selections. The players also receive visual information regarding their selection from the Reactable: if the selection is correct, the selected pair blinks with a green color and the object (but not the category) dissapears whereas the pair blinks with a red color if the selection is incorrect. The game was tested with both children and adults and the contents were adapted according their estimated knowledge. Therefore, for the children the game's topic was recycling, where the task was to correctly match different types of waste to the corresponding recycling bin. For the adults the topic was geography, where the task was to correctly match a capital with the corresponding country.

The learning scenario requires turn-taking and comprises three levels of increased difficulty. Both the human and robot had the same objects mirrored in each side. At each level, they had to correctly match the four objects to their corresponding category to proceed to the next level. The gradual increase of the difficulty allows for the scaffolding of the task, and consequently for the improvment of the learning process [4]. As mentioned earlier, the game was realized using the Reactable; the virtual objects were projected on the Reactable and object selection was achieved either with the usage of an object or with a cursor (fingertip). At the beginning of the interaction, the robot verbally introduces the game and is the first who initiates the interaction and the game.

4.2 Methods

We hypothesized that the combination of eye-contact and facial expressions strengthens the feedback between the player, the participant and the participant's choice, and affects the participant's subjective experience. As a result, we expected that when exposed to both behavioral conditions the participants would have a higher both knowledge transfer and the subjective experience.

To test our hypothesis and assess our architecture, we devised five experimental conditions (see Table 1) where we varied the gaze behavior and facial expressions of the STA. The experimental conditions are: Not-oriented Robot (NoR) (fixed gaze at a point - this way we are ensured that no eye contact is achieved); Task oriented Robot (ToR) (gaze supports actions, without making eye contact or showing facial expressions); Task and Human oriented Robot (T&HoR) (gaze supports actions, eye contact and showing facial expressions); Table-Human Interaction (THI), where the participant plays alone with the Reactable, and the Human-Human Interaction (HHI), where the participant plays with another human. Apart from the HHI, the behavior of the STA in terms of game play, verbal interaction and reaction to the participant's actions remained the same. The aim of the THI condition is to show the importance of embodiment of the STA during the interaction; the HHI condition acted as both the control group and a way of achieving a baseline regarding the interaction. The children were tested in the NoR, T&HoR and HHI conditions whereas the adults in all conditions.

Data were collected within three systems: knowledge and subjective experience questionnaires, behavioral data and the logs from the system. Participants had to answer pre- and post- knowledge questionnaires related to the pairing game. For recycling, the questionnaires had a total of twelve multiple-choice questions, including the same wastes and containers that the participants had to classify during the game. The information for creating this questionnaire came from the website "Residu on vas" (www.residuonvas.cat), property of the Catalan Wastes Agency. For geography, the questionnaires had a total of 24 multiple-choice questions (half of them, about the countries and capitals and the other half, about countries and flags). These questionnaires were given to the participants before and after the game, in order to evaluate their previous knowledge about the topic and later compare the pre- and post- knowledge results. The subjective experience questionnaire aims at assessing the STA's social behavior. It consists of 32 questions based on: the Basic Empathy Scale [26], the Godspeed questionnaires [5] and the Tripod Survey [17]. In the case of adults, there were 74 participants (age M = 25.18, SD = 7.55; 50 male and 24 female) distributed among five different conditions (THI=13, NoR=15, ToR=15, T&HoR=16, HHI=15). In the case of children, we tested 34 subjects (age M = 9.81, SD = 1.23; 23 male and 11 female) who randomly underwent three different experimental conditions (NoR=12, T&HoR=14, HHI=8).

Table 1. Table of the five experimental conditions.

	Embodiment	Action supporting gaze	Eye contact	Facial Expression
THI	No	No	No	No
NoR	Yes	No	No	No
ToR	Yes	Yes	No	No
T&HoR	Yes	Yes	Yes	Yes
HHI	Yes	Yes	Yes	Yes

Various conditions of robot behavior based on the interaction scenario

4.3 Results

First, we report a significant knowledge improvement in adults for all the conditions: THI, t(13) = 7. 697, p <0.001; NoR, (t(14) = 2.170, p = 0.048; ToR, t(14) = 3.112, p = 0.008, T&HoR, t(16) = 3.174, p = 0.006 and HHI,t(13) = 3.454 p = 0.004. In constrast, in children, there was no significance between conditions, although our results suggest a trend in improvement. We expected a difference among conditions, as we hypothesised that in the T&HoR condition, the knowledge transfer would be greater than the rest of the conditions. However this does not occur in neither the adult nor the children scenarios. In the case of children, we hypothesized that the associations were too simple; in the case of the adults, it seems that the knowledge transfer was achieved irregardless of the condition, suggesting that possibly the feedback of the Reactable itself regarding each pairing (green for correct and red for incorrect) might have been sufficient for the knowledge to be transferred.

Regarding the subjective experience, there was no statistical difference in the questionnaires data from children. We suspect that such result might be affected by the fact that both the Empathy and Godspeed questionnaires are designed for adults, and not children. In adults, although there was no significant difference among conditions for the Empathy and Tripod parts, there was a statistically significant difference between groups for the Godspeed part, as determined by one-way ANOVA (F(4,35) = 4.981, p = 0.003). As expected, humans scored higher (HHI, .06 $\pm$ 0.87), than the robot in two conditions (NoR, 2.84 $\pm$ 0.72, p = 0.003; ToR, 3.19 $\pm$ 0.46, p = 0.044, but surprisingly not in the T&HoR) and the table (THI,3.02 $\pm$ 0.56, p = 0.031) (Bonferroni post-hoc test). We can therefore hypothesize that the STA significantly scores lower than a human in all conditions but the one where its behavior is as close as possible to that of a human: gaze that sustains action (look at where the agent is about to point) and is used for communication purposes (look at human when speaking) and facial expressions as a feedback to the humans actions.

Regarding the behavioral data, there was a statistically significant difference between conditions for the mean gaze duration in children (one-way ANOVA (F(2,26) = 8.287, p = .0021)). A Bonferroni post-hoc test revealed that the time spent looking at the other player (in seconds) was significantly lower in the NoR (14.70 $\pm$ 8.81", p = 0.012) and the HHI conditions (11.74 $\pm$ 8.02", p = 0.003) compared to the T&HoR condition (30.97 $\pm$ 15.16")(figure 3). Our expectation regarding the difference between the NoR and T&HoR conditions was correctly met: people looked more at the agent who looked back at them. However, we were not expecting a difference between T&HoR and HHI condition. We believe that the reason why the difference in mean gaze duration occurs is because humans remained focused on the game and were mainly looking at table instead of looking at the other player. Furthermore, there were much less spoken interactions between them. In contrast, in the rest of the scenarios, the STA would comment on the actions of the participant, attrackting attention in more salient way.

In adults, a Kruskal-Wallis test showed that there was a high statistically significant difference in the time spent looking at the other player between the different conditions, x2(4) = 15.911, p = 0.003. The results of the Mann-Whitney Test showed significant differences between the THI (2.72 $\pm$ 5.53) and the NoR (16.37 $\pm$ 21.17) conditions (p = 0.026); the THI (2.72 $\pm$ 5.53) and the ToR (7.80 $\pm$ 7.76) conditions (p = 0.029); the THI (2.72 $\pm$ 5.53) and the T&HoR (19.87 $\pm$ 12.01) conditions (p <0.001); the ToR (7.80 $\pm$ 7.76) and the T&HoR (19.87 $\pm$ 12.01) conditions (p = 0.028); and the T&HoR

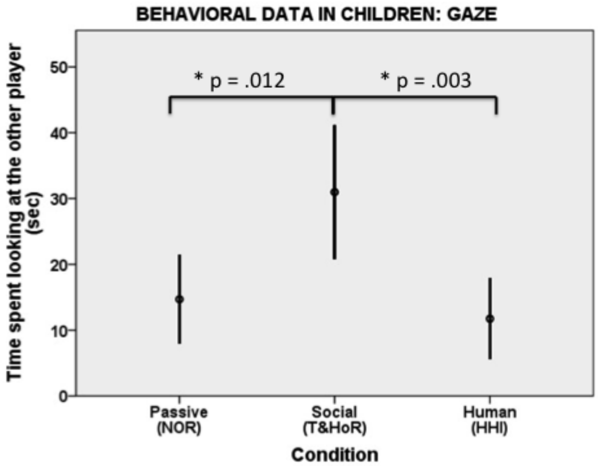

Figure 3. Time spent looking at the other player (in seconds) in children among conditions. Asterisks "*" depict significance.

(19.87 ± 12.01) and the HHI (3.66 ± 4.13) conditions (p = 0.002) (See figure 4). As expected, the more human-like the behavior of the STA, the more people would look at. The explanation regarding the difference between T&HoR and HHI in gaze duration is similar to that of children.

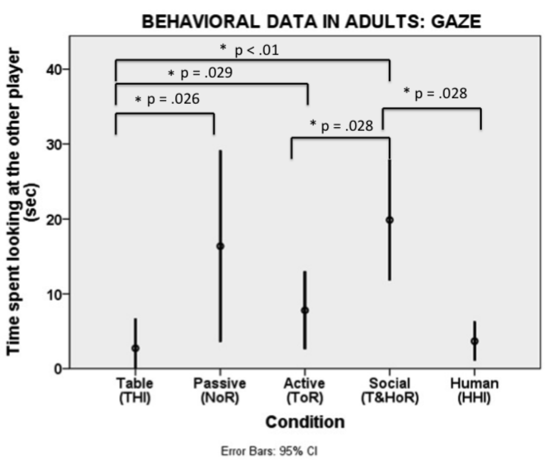

Figure 4. Time spent looking at the other player (in seconds) in adults among conditions. Asterisks "*" depict significance.

5 DISCUSSION AND CONCLUSIONS

The goal of the present study is to provide the key implementation features of the Synthetic Tutor Assistant (STA) based on the DAC architecture. Here, we propose the implementation of the STA within the DAC, a theory of the design principles which underlie perception, cognition and action. DAC is a layered architecture (Soma, Reactive, Adaptive and Contextual) intersected by three columns (world, self and actions), modeled to answer the H5W problem: Why, What, Where, When, Who and How. We explain the basic layers of DAC and focus on the Reactive Layer that constructs the basic reflexive behavioral system of the STA, as systhematically explained in section 3.1.

DAC predicts that learning is organized along a hierarchy of complexity and in order to acquire and consolidate new material the learner undergoes a sequence of learning phases: resistance, confusion and resolution. We argue that it is important to effectively adjust the difficulty of the learning scenario by manipulating the according parameters of the task (Adaptive Layer). This function will allow us for controlled manipulation of confusion, tailored to the needs of each student. Though it is not in the scope of the present study, in the future we plan to adjust the parameters of the learning scenario studied here on the basis of an online analysis of the learners' performance, interpreted both in terms of traditional pedagogical scales and the DAC architecture (Adaptive Layer). The learner's errors and achievements will be distinguished in terms of specific hierarchical organization and dynamics. Finally, the Contextual Layer will monitor and adjust the difficulty parameters for both individual students and bigger groups on a longer time scales. The motivational system presented is mainly focused on the Reactive Layer of the architecture, but our aim is to primarily adapt the Reactive Layer to the needs of STA and teaching scenarios and then extend the STA to include the Adaptive and Contextual Layers.

We devised an educational scenario to test the implementation of the STA-DAC as well as to evaluate the effectiveness of different social features of the robot (social cues such as eye contact and facial expressions). The task devised was a pairing game using the Reactable as an interface, where the robot acts as a constructivist tutor. The pairing consisted of matching different types of waste to the corresponding recycling bin (recycle game) for the children and matching the corresponding capital to a country (geography game) for the adults. The learning scenario was turn-taking with three levels of increased difficulty. The experiment consists of five different conditions, described in section 4.2: THI, NoR, ToR, T&HoR and HHI. Adults were tested in all conditions whereas children in NoR, T&HoR and HHI. To assess the interaction, the implementation as well as the effectiveness of the robot's social cues, behavioral data, logged files and questionnaires were collected.

In the results, we see that in adults, there are significant differences in knowledge improvement among conditions. On the other hand, there is a trend in knowledge improvement in children, but it is not significant. The results are not sufficient to draw any concrete conclusions about knowledge retrieval. Nevertheless, we can see that people scored higher in the post-experiment questionnaire, on the other hand, results are not enough to identify exactly the reason. It is possible that the task, though the difficulty increased on each trial, would still remain relatively easy. That is why we aim at devising a related experiment where we would exploit the Adaptive Layer that adapts the difficulty to each individual player.

Our results show that children looked more at the T&HoR robot than then ToR or HHI. Based on these results, we can conclude that the behavior of the Task and Human oriented Robot drew more the attention of the participant than the other human or the solely Task oriented Robot. The robot was looking at the participant when it was addressing him; its gaze followed both the player's and its own actions, meaning that it would look at the object that the participant had chosen or the object that it chose. Finally, it would show facial expressions according to each event: happy for the correct pair or sad for the incorrect one. Such cues may indeed be more salient and draw the attention of the player. In all conditions, the robot was speaking, so it seems that it was the implicit non-verbal communicative signals of the robot that drew the attention of the participant. In the case of the adults, the results are also similar. Such behavior is important in the development of not only social but also educational robots, as gaze following directs attention to areas of high information value and accelerates social, causal, and cultural learning [1]. Indeed, such cues positively impact human-robot task performance with respect to understandability [7]. This is supported by results like the ones of [24], where the addition of gestures led to a higher effect on the participant only when the robot was also performing eye contact.

Finally, the results from the Godspeed questionnaire in adults show a significant difference in the overall score between HHI and THI, NoR, ToR but not the T&HoR. Such results were generally expected, as a human would score higher than the machine. In children, there was no significance in any of the conditions, however, it may be the case that the Godspeed questionnaire is not the optimal measurement for subjective experience, at it may contain concepts that are not yet fully understood by such a young age. Perhaps simpler or even more visual (with drawings that represent the extremes of a category) questionnaires would be more appropriate.

Though the knowledge transfer results are not sufficient to draw any concrete conclusions (as the knowledge transfer is not significantly different among conditions), the complex social behavior of the robot indeed attracts attention of the participant. As for the pilot study, the authors need to focus more on the evaluation of the system, and need to introduce a strong experimental design to derive more specific conclusions. Further analysis of the behavioral data can provide insight regarding eye contact in terms of error trials, decision time and task difficulty. In the upcoming experiments we will provide a better control in the HHI condition. A possible strategy is to deploy a specific person (an actor) as the other player, to normalize the characteristics of the scenario between all the subjects.

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