Let Me Guide You!
Pedagogical Interaction Style for a Robot in Children's Education

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Abstract. Social Robots are increasingly applied in healthcare and education. Pedagogical Agents (PAs) are being developed to adapt to the users knowledge, and efforts are made in strategic action selection: *what* action is appropriate given the context and user preference. However, the issues of *how* these actions can be appropriately communicated receives less attention. In this paper we propose the development of an adaptive pedagogical interaction style for a robot. We discuss the role of style in human-human interaction and the lack thereof in human-robot interaction. While human educators heavily rely on their ability to identify and respond accordingly to social signals in a fluent and natural way, robots cannot adapt their style of interaction effectively. By adapting the pedagogical interaction style of a robot to the learner and context we expect to be able to create rich and fruitful personalized educational interactions and ultimately facilitate social bonding between the learner and robot. In this position paper we present our view as a starting point for the management of this interaction style. As a basis for the proposition, pedagogic and motivational theories are used.

Keywords: Social Robots, Child-Robot Interaction, PAL, Healthcare, Education, Pedagogical Agent, Interaction Style.

1 Introduction

As robots will emerge in the social and private domain, robots begin to collaborate with humans who are not trained to do so. These socially interactive robots are defined by their ability to express and perceive affect, communicate in high level dialog, learn user models, establish and maintain social bonds, use natural cues, express personality and develop social skills [13]. The importance of social intelligence for robots is stressed, and thereby the need for development of robots able to identify, understand and respond to human communication [17]. Usage of social robots range from assistive robots in elderly care, to tour guides, to educational support. We focus on educational robots, namely, our research is centred around the development of a personal assistant for a healthy lifestyle (PAL) to study long-term child-robot interaction. The (NAO) robot is intended to support children with diabetes mellitus type 1 (T1DM) in extra-curricular self-management education.

According to Mubin et al. [27] an educational robot can, dependent on the content and student, fulfil the role of tool, co-learner or mentor. Moreover, the style of interaction is dependent upon task and user age. In general, educational robots should take into account or adapt to the age and requirements of the learner, suggested is consideration of the learners characteristics such as age, gender and background. [27] We believe that aside these more general attributes, characteristics specific to the educational context should be taken into account. When humans perform educational tasks, they need not only pay attention to the content, but also (unconsciously) select how to communicate the information; they approach the learner in an individual stylized manner (e.g. empathic or direct). The ability to recognize and act upon social cues is crucial for effective and motivating educational interaction. Therefore, social robots employing educational roles should have some kind of interaction style management. We define interaction style as the way in which information is expressed; *how* interaction is formed, displayed by a combination of behaviours that evoke a perceived (NAO) robot intent to influence the user. For example, a request to close the window can be communicated in a comforting, empathic style, expressed through a soft voice, subdued movement and question asking, or by a direct, agitated style, expressed through raised volume, big gestures and statement provisioning. In recent years, pedagogical agents are developed adapting their role to the perceived level of knowledge [7, 32, 19] or affective state of the user [16, 29, 5]. Some have investigated generalized effect of educational strategies on the interaction itself and outcomes such as learning gains [3, 24, 28]. The results of these studies indicate that people are able to detect and respond differently to different robot roles, but little is known about the influence of individual user preferences on these effects. A recent study showed that interaction style could actually influence task performance in collaborative play [8]. A pilot study showed a positive influence of content personalization on enjoyment, motivation, learning effect and interaction intensity [18]. We argue that, for educational robots to become truly personalized, adaptive social collaboration partners, not only affective expression and generalized action selection need to be pursued, but also the personalized and contextualized style of communication aligned to user preferences in learning and interaction needs to be addressed.

In this paper, we propose a model for pedagogical interaction style for educational robots. Based on theory of motivational interviewing and learning style we introduce a pedagogical interaction style that is context sensitive and adaptive to the user model, spanning over long-term usage and seconds. With this approach our future work aims to provide the possibility to create personalized and appropriate robot behaviour supportive to socially intelligent human-robot interaction that facilitates social bonding. The paper is organized as follows. Section 2 provides a brief summary and discussion of the state of the art in social robots and pedagogical agents. In section 3 theoretical background of human-human educational interaction is highlighted. Afterwards, the model for pedagogical interaction style is introduced and exemplarily explained by its usage in PAL. Lastly, concluding remarks are presented in section 5.

2 Related Work

In this section we focus on studies and related work from two relevant fields, namely social robotics and pedagogical agents (PA). Although PAs are mostly concerned with virtual presentation of instructional agents, work on modelling and expression of agent behaviour is of relevance to the development of a robot instructor.

2.1 Strategic Behaviour Selection and Evaluation

Different perspectives are taken on what is appropriate behaviour, and how this behaviour is to be strategically selected. In recent work, the behaviour of a (virtual) agent is often predetermined based on role or mapped to a perceived user state.

Based on theory of constructivism and zone of proximal development, Smith and Affleck [32] developed a virtual agent to support programming learning, selecting the agents function (*facilitator*, *tutor*, *advisor* or *pseudo-student*) aligned with the perceived level of knowledge. In an interview skill training simulation for police officers, interpersonal stance (degree of dominance and affect) is used to model convincing affective responses for an embodied conversational agent (ECA) [5], evaluation showed that users are able to recognize a persona expressed by the ECA [6].

A virtual and physical (iCat) instructor, designed to support self-help and motivation, fulfilled the roles of a: *buddy* asking about well-being and showing empathy, *educator* informing and asking about health and *motivator* asking about and providing feedback on desired changes [25], no difference in motivation and learning effect was shown in child-robot interaction [24]. In another project children participated in collaborative play with a (NAO) robot designed either as *peer* based on collaborative behaviour or *tutor* based on scaffolding support [35], in difficult tasks the peer condition showed higher task effectiveness and performance compared to the tutor [8].

An attempt to develop an emotional responsive virtual tutor in STEM education is made in AutoTutor [16]. The agent detects typical learner affective state (confusion, frustration, boredom, interest, excitement or insight) and accordingly adapts its action (feedback, pump, prompt, hint, assertion, correct, answer, summarize) to maximize learning effect. Emotional expressions through facial expression, prosody and posture modulation were added to engage the learner in a human-like, natural interaction [11]. Criticism is expressed on the straight forward strategy selection based on learners current affective state, an optimized PA should actively attempt to steer the learner into affective states correlated with positive learning effects and prevent negative once [11]. A field study with an educational (Robovie) Robot learning English to Japanese children showed the robots ability to teach English by informal education [20]. The robot was able to recognise the user and called the user by name to encourage interaction, some positive effects are reported. Interest declined after one week, learning gains were observed for those individuals who maintained interacting in the second week. The authors suggested that bonding facilitates learning gain, however, it is unsure if maintained interaction is the result of bonding or interest in English learning. Moreover, no comparisons are made with other teaching methods.

2.2 Affective Bodily Expression

If we are able to develop a model to select appropriate behaviour, this behaviour must be convincingly expressed by the agent. Up until now, most research has been focusing on emotion modelling and expression.

Human emotion is often expressed though voice, facial expression, gestures and bodily movement [23]. Paiva et al. [30] argue that emotions are essential for interactions that resemble human-human interactions and that appropriate display of affective state positively effects user involvement. Moreover, to be perceived as socially intelligent, the agent must not only convey believable expressions, but also be able to do so in an intelligent and personalised manner by gradually adapting their affective behaviour to the particular needs and preferences of the user [30]. Individuals differ considerably in encoding and decoding of emotional signals, and have different styles preferring certain gestures as well as modalities they use. Current development of ECAs are based on either general trends or averages from multiple individuals [23]. For example, Ball and Breese [2] directly mapped arousal to size and speed of gestures, and valance to voice pitch to generate ECA responses aligned to the emotional state of the user. In EMOTE realization of emotions by shape-effort analysis from Laban movement analysis is proposed [9]. An attempt to capture individual differences by integration of user personality into the ECAs mental state is done in PARSYS [1] and GRETA [26], in the latter the ECAs baseline personality, expressed by default parameters for gestures, is dynamically modified based on communicative intentions of the ECA.

Humanoid robots often have simple faces and thus rely mainly on bodily expression of emotion, which are suggested to be more difficult to decode [30]. However, anger, sadness and joy are reported to have equally accurate recognition rates for facial expression and static posture [23]. An experimental study showed that children can recognise emotion expressed in static robot posture, the following recognition rates are reported: fear (87.5%), happy (89.28%), angry (96.43%), sad (67.86%) and surprised (68.75%) [10]. Affective expression of a social robot by bodily movement in one-to-many interaction is researched in [34] where a humanoid (NAO) robot gave a lecture in an actual course on robotics. Co-verbal gestures of the robot were modulated to express either positive or negative valance. Participants reported no difference in perception of the robot, indicating that participants do not consciously recognize the robot mood. However, the experiment indicated that gesture modulation does influence participant behaviour: self-report for arousal was higher for participants who received a lecture from the positive robot and video annotation showed increased valance and arousal of the audience in the positive mood condition. No effects on task-performance are reported.

3 Human-Human Pedagogic Interactions

Human educators heavily rely on, and therefore are trained in, strategic use of interaction style to create effective educational interventions. They continuously adapt their behaviour to the individual needs of the learner and context. In this section we review several theories that underlie this process of adaptation.

3.1 Motivational Interviewing

In healthcare, three communications styles are defined: *directing*, *guiding* and *following*. The directing style is used when giving straightforward advice. A following style can be appropriate to support a patient e.g. during moments of negative emotions. The guiding style is suited for difficult conversations about behaviour change. Three core communication skills are defined: *asking*, *informing* and *listening*. All skills are required for each style, however, there occurrence varies. Moreover, content and phrasing indicate communication style. Motivational Interviewing (MI) [31] can be regarded as refined, goal-oriented form of guiding; counselling aimed at long-time behaviour change by influencing intrinsic motivation for change. The core principle of MI is to understand and evoke the patient's motivation and empowering the patient in behaviour change by exploration of pros and cons of alternatives. The conversation spirit should be collaborative, evocative and honour the patients autonomy; rapport is used to resolve the patients ambivalence about behavioural change.

3.2 Experiential Learning Theory

Experiential Learning Theory (ELT) [21] is based on commonly accepted propositions of learning to: be a process, be holistic, require conflict resolution, result from interaction with the environment and is a process of creating knowledge (constructivism). In the ideal process of learning the learner repeatedly progresses through a cycle of: *experience*, *reflection*, *conceptualize & generalization* and *acting on new knowledge*. ELT proposes that the idealized learning cycle varies by individuals' learning style and learning context. Kolb identified four learning styles describing a preference for different phases of the learning cycle: *diverging*, *assimilating*, *converging* and *accommodating*. All people learn best when shifting trough different phases, however, learners tent to enter the cycle at a preferred point; the relation between learning style and according preference is depicted in Figure 1a. Learning style is influenced by the learners personality, but also by environmental factors such as: educational specialization, roles and tasks [22].

3.3 Theory of Multiple Intelligences

The Theory of Multiple Intelligences (MIT) originally identified seven relatively independent forms of information processing that differentiate in sensory modalities: *logical–mathematical*, *linguistic–verbal*, *visual–spatial*, *musical–rhythmic*, *bodily–kinaesthetic*, *interpersonal–social* and *intrapersonal–self-knowledge* [15]. Gardner suggested that individuals differ in their profile of intelligences and will benefit from education wherein teachers use methodologies and activities to serve all students opposed to only those who excel at linguistic or logical intelligence [14], leading to an increased feeling of engagement and competence. Despite the broad criticism on Gardner's work his theory is adopted in many educational settings and used to describe learning preferences.

VARK Model. VARK [12] is an acronym for Visual, Aural, Read/write and Kinaesthetic, it references to the preference learning modality; the way information is presented. This preference is not fixed but stable over medium-term and can be identified by both learner and teacher. Information communicated aligned with preferred modality is likely to result in better understanding, higher motivation and deeper learning.

3.4 Leary's Rose

Leary's Rose (see Figure 1b) —also known as the interpersonal circumplex—is a model for human interactional behaviour defined by two axes: *dominance* and *affect*. The horizontal affective-axis depicts willingness to cooperate. The vertical dominance-axis tells to what degree someone is dominant or submissive. The axes divide the rose into four quadrants, of which each half indicating an interpersonal style. Leary's theory states two interaction rules: above-below are complementary and opposed-together are symmetric, meaning that, for example, opposed behaviour evokes opposed behaviour and above behaviour evokes below behaviour [33].

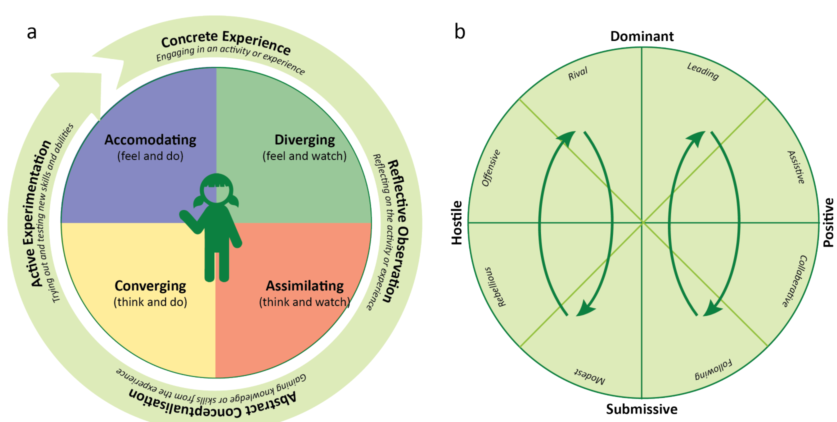

Fig. 1. a: Kolb's learning phases and related learning style preferences. b: Leary's interpersonal stances with the direction of interaction rules.

4 Adaptive Pedagogical Interaction Style for Robots

To create personalized human-robot interactions the robot must be knowledgeable about the users state and context and have the ability to respond appropriately [4]. In the related work section some advancements on adaptation and strategic behaviour selection are presented. To the best of our knowledge no attempts are made to personalise robot behaviour based on user preference of learning style. For example, AutoTutor adapts to the perceived user emotion, not to learning style preference. What we believe is needed is a) a list (or ontology) of interaction styles, b) a validated way to express these styles in robot behaviour, c) to find out which style is a-priori appropriate (for who and when), and d) adapt the style if metrics (interaction intensity) show we did not select the best/appropriate style for a particular person at a particular moment. In this section we propose a model for adaptive pedagogical interaction styles for educational robots.

We envision a robotic educator who adapts its behaviour to learner preferences and is sensitive to context; based on the user model and contextual factors an interaction style with a high likelihood of appropriateness is selected and expressed, the active choice is continuously evaluated and if necessary adjusted. Continuous evaluation of appropriateness support online adaptation and enables learning over time the user's preferences for interaction style.

4.1 PAL for Children Diagnosed with T1DM

We now explain our approach in more detail by an example in healthcare education for children diagnosed with diabetes mellitus type 1 (T1DM) in need of self-management training.

For the sake the example, we define three educational roles: *expert*, *mentor* and *companion*, and we adhere to the three communication styles presented in [31]: *guide*, *direct* and *follow*. Based on the user model a likely appropriate robot role and communication style are selected; the pedagogical interaction style is defined by the combined selected role and communication style and expressed in the robots behaviour. The user model consists of knowledge of user preferences (e.g. developmental stage, learning style and interpersonal stance) and dynamic perception of the user state (e.g. affective state, interaction intensity and motivation). Moreover, contextual factors such as the current location, users and activity are to be taken into account. Continuous evaluation of the interaction (intensity) is necessary to be adaptive and ensure appropriateness. This implies the system has a memory and is capable of real-time detection of influencing factors. For each interaction style output behaviour is defined; this includes activity selection and expression of style by e.g. speech act, body posture, mood modulation etc. However, contextual factors also have a direct influence on output behaviour; asking a question is never considered appropriate in a classroom setting during a test.

Imagine a child (Robin) aged 7 prior to an important soccer game. Robin surely wants to be on the field, but knows this will only be allow this if the blood sugar measurement is good. Taking no risks Robin decides to write down a fake measurement. PAL, Robin's personal support Robot, noticed that Robin changed the values, PAL knows that Robin has a learning goal to manage diabetes during sports, what should PAL do? Having the knowledge that Robin lacks insight in consequences of bad blood values during sports, PAL should educate Robin on this and provide necessary information: the expert role is selected. Guiding is the a priori preferred communication style thus the *Expert-Guide* interaction style is selected and PAL proposes to play an educational quiz. However, PAL notices that the interaction intensity is very low, and believes that Robin is sad; knowing that Robin prefers empathic interaction conveyed in the companion role when feeling sad, PAL changes to the *Companion-Guide* interaction style and starts a conversation about sports asking Robin about his likes and dislikes regarding his illness and soccer. When one of Robins friends enters the room PAL detects this change in users. Robin has a self-management goal to learn to talk about his disease with friends, but because of the perceived negative affective state PAL decides that now is not the right time; PAL obeys to Robins preference, changes to the *Companion-Follow* style and pauses interaction.

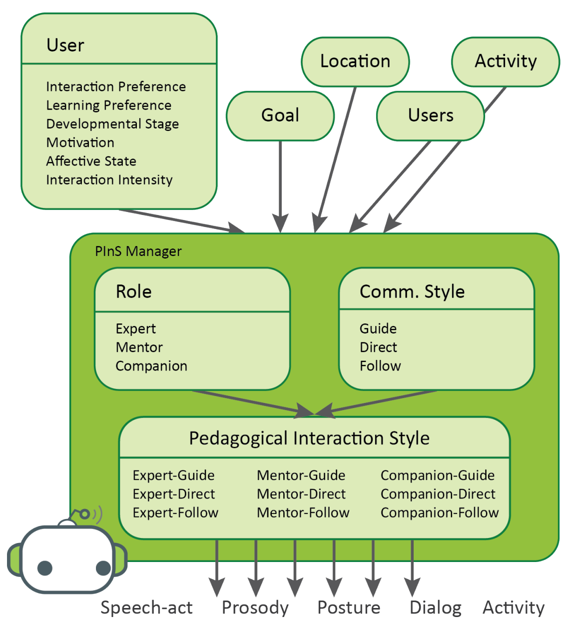

Fig. 2. Model for management of pedagogical interaction style depicting factors (user, goal, location, users and activity) influencing selection of role and communication style, that together determine which pedagogical interaction style is chosen, which is then expressed in robot behaviour using, for example, prosody, speech and posture. (contextual factors and behaviours are included for illustration purposes only.)

5 Conclusion/Discussion

We have argued for the need of educational robots that can adapt their interaction style to individual users. We have reviewed approaches that adapt the robot's role and learning content based on the child's state, but these approaches do not try to measure and adapt to the preferred interaction style of the user. To explain our position, we have shown using an abstract model, how this personalized interaction style could be generated.

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