Identifying Task Engagement: Towards Personalised Interactions with Educational Robots

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***Abstract*—The focus of this project is to design, develop and evaluate a new computational model for automatically detecting change in task engagement. This work will be applied to robotic tutors to enhance and support the learning experience, enabling timely pedagogical and empathic intervention.**

This work is intended to forward the current state of the art by 1) exploring how to automatically detect engagement with a learning task, 2) designing and developing new approaches to machine learning for adaptive platform-independent modelling and 3) evaluation of its effectiveness for building and maintaining learner engagement across different tutor embodiments, for example a physical and virtual embodiment.

***Index Terms*—engagement; human-robot interaction; robotic tutors; social robots;**

I. Introduction

The term engagement is often used in human-robot interaction (HRI) to explain the connection between the human and the robot during an interaction [1] [2] [3] [4]. However, in this work the focus is to design, develop and evaluate a new computational model for automatically detecting and maintaining engagement with a learning task. Here, engagement with the learning task is considered to be characterised by elements of attention, concentration and enjoyment [5].

Imagine the typical classroom scenario where twenty-five or more children are being taught by a single teacher, where each child is only benefiting from a fraction of the teachers' time and assistance. Now, again imagine the same scenario, but this time each of the children is learning through an interactive touch-screen table (Figure 1), designed to be adaptive and supportive of the child throughout the learning experience. Attached to the table is a humanoid robotic tutor capable of both emotional and pedagogical intervention, applying teaching styles and strategies which are suitable and personalised to each child.

This could be the future of education... More one-to-one interactions in the classroom and learning experiences which are tailored towards the child, promoting their strengths and abilities whilst also working towards overcoming their weaknesses.

If only it was that simple... The problem here is that in addition to the knowledge of the subject matter, human teachers have socio-emotional and empathic abilities which they can use to assess whether or not a child is engaged and whether they are showing adequate progression in the learning task. Replicating these traits within a robotic tutor requires extensive amounts of interdisciplinary research to recognise and understand the behavioural and contextual indicators of engagement.

This research will inform the development of a new computational model to automatically detect the learners' state of engagement and to distinguish how much is attributable to the task in comparison to that owing to the social bond with the robot. This model will feed-forward to parallel reasoning systems, providing an informative physiological view of the learner in terms of behavioural, emotional and cognitive state. This state and any pedagogical, socio-emotional and empathic interventions used to support and scaffold the interaction will feed-back into a personalised model of the learner, further enhancing its ability to predict, improve and maintain future states of engagement.

The success of this project is dependent upon three key aspects: 1) being able to automatically detect the learner's engagement with the task, 2) being able to adapt and balance the level of challenge, perception of user-control and the aesthetic/sensory appeal of the task (i.e. on-the-fly) [6] and 3) being able to trigger the correct behaviours and interventions in the robot to build and maintain the engagement [7].

In this project behavioural and contextual indicators such as the learner's affective state, progress within the task, and touch screen gestures [8] will be explored in fine detail.

II. Related Work

Recent research in HRI has shown that social and task context play an important role in engagement [9], where engagement was successfully predicted from context logs. Additionally, recall performance was improved using an adaptive agent which monitored and improved student attention when engagement decreased [10], concluding that agents need to be able to measure and respond to user states if to be integrated in general HCI. Kapoor and Picard [11] used multi-modal Gaussian process to classify interest in a learning scenario; with this in mind, data fusion offers very promising results which need to explored further. Sanghvi et al. [12] use human posture and body motion to detect engagement, which again shows much promise and might be reproducible using a visual sensor.

Student engagement is a mix of several components 1) Behavioural: persistence and participation, 2) Emotional: interest, value and valence, and 3) Cognitive: motivation, effort and strategy [13]. Engagement is strongly related to achievement and development [14] [15]. Furthermore, engagement is shown to be a major contributing factor in the promotion of both short and long-term learning performance [16].

A substantial amount of work has been dedicated to studying social learning (i.e., learning in a social context) using robots [17]. Of late, the use of robots as tutors in educational scenarios has started to attract a lot of attention [18] [10]. Nevertheless, often these tutors either are not fully autonomous, or are endowed with limited adaptation and user personalisation abilities. Moreover, experimentation has mainly taken place in controlled environments, rather than in real classroom scenarios.

III. Methodology

A. Experimental Framework

This project is reliant on both the social and situational context in which the task occurs, therefore, experiments will be carried out within the framework of a larger project involving several partners, and more specifically, a showcase developed in the area of geography with 11-13 year old secondary school children. This framework forms an integration of interdisciplinary research on affect recognition, learner models [19], adaptive behaviour and embodiment for human-robot interaction in learning environments [20], grounded in psychological theories of emotion in social interaction and pedagogical models for learning facilitation.

Therefore, this project can specialise in the core area of automatically detecting and modelling task engagement.

B. Hypotheses

The purpose of the research described in this paper is to identify and automatically recognise learner engagement, therefore, to help inform this and future work we have three working hypotheses: 1) engagement can be automatically detected and modelled with behavioural and contextual indicators, 2) behavioural and contextual indicators of task engagement can be distinguished from those attributed to social engagement, and 3) modelling engagement supports a personalised learning experience leading to an increase in learning performance.

C. Research Plan

1) Pilot Study: Working in collaboration with psychologists we will carry out three experiments to explore and identify the most relevant behavioural and contextual indicators of user engagement. The experiments will include engagement - with a task, with a robot (i.e. social engagement) and a combination of the task and robot together.

In addition to the contextual data derived from the task interaction, a corpus will be collected from the study and used in the development of the computational model of engagement. Video recording equipment will capture the human-task and human-robot interaction to be coded off-line, face recognition software will be used to extract facial expressions, head direction and gaze in real-time; and electro-dermal readings from a Q Sensor[1] will be used to record arousal in real-time.

In the first experiment the robot will not be present as we only wish to measure engagement with the task. We intend to elicit two different states of engagement using a whack-a-mole style game to induce high levels of engagement and a far more non-engaging touch button control task for inducing low levels of engagement. We will have two groups of participants and two conditions. The conditions are 1) play the engaging whack-a-mole style game followed by the non-engaging control task; and 2) undertake the non-engaging control task followed by the more engaging whack-a-mole style game. Both groups will undertake the engaging and non-engaging tasks, but one group will play the engaging task first and the other will undertake the controlled task first.

In the second experiment we intend to explore social engagement with the robot. Here, the participant will be asked to carry out a sequence of tasks to construct a battery object on the multi touch table and the robot will behave differently to form two different control conditions. In the first condition the robot will be helpful and instructive, attempting to help with the task and signifying the importance of having "their" battery finished. Whereas, in the second condition the robot will display disinterest in the task and does not try to establish a bond with the participant.

In the third experiment we will explore task and social engagement using four conditions: 1) a helpful and instructive robot with an engaging task, 2) a helpful and instructive robot with a non-engaging task, 3) an unhelpful and non-instructive robot with an engaging task, and 4) an unhelpful and non-instructive robot with an non-engaging task. Both engaging and non-engaging tasks will be similar if not identical to that used in the first experiment.

2) Wizard of OZ Study: The second milestone of this work is to build upon what was learned from the pilot study with more refined learning content and teaching strategies within a geography showcase. This stage will include a Wizard-of-OZ study in a real class environment, with learning content having been informed and supported by teaching experts. The wizard will control the robot from another room so the participants perceive the robotic tutor as a socially capable interactive partner.

The study will include video recordings of children's behavioural expressions, contextual information relating to the learning task, and data from other sensors.

[1] http://www.qsensortech.com/, Affectiva Q sensor, Last accessed 25-4-2013

Fig. 1. Robotic tutor with task running on interactive touch-screen table.

3) Learner Modelling: In this project each learner is modelled individually to personalise the learning experience. The learning task can be adapted towards the strengths of the learner whilst also recognising and confronting their weaknesses.

Here, we intend to explore different pedagogical and socio-emotional strategies, such as guided versus discovery learning, different in-task strategies and robotic tutor interventions.

At this stage in the project the learner's abilities and difficulties will be measured in terms of progress within the learning task. Working in collaboration with a fellow student, we intend to jointly investigate the development of a platform-independent learner model to encompass all aspects of the interaction with the platform. This will be a feed-forward and feed-back design where engagement states are combined with appropriate actions and valued accordingly. This work will cover different interactions across both physical and virtual embodiments of the tutor. This will inform the design and development of new approaches to machine-learning, uncovering relationships between the task, engagement states and learning progress.

4) Evaluation: The learner model and engagement detector will be integrated with the robotic tutor and experiments will be used to test our approach. Evaluation will follow an iterative process. Wizard-of-Oz experiments will be followed by a full evaluation of tutor's prototypes exhibiting autonomous behaviour in a real-world classroom environment. The evaluation will aim at assessing the effectiveness of the personalised robotic tutors as pedagogical tools for learning.

IV. Contributions to Affective Computing

This work intends to forward the current state of the art by 1) exploring how to automatically detect engagement with a learning task, 2) designing and developing new approaches to machine learning for adaptive platform-independent modelling and 3) evaluation of its effectiveness for building and maintaining learner engagement across different tutor embodiments, for example a physical and virtual embodiment.

Grounded in both social and situational context, this interdisciplinary research aims to push the boundaries of current understanding in terms of both technical and theoretical aspects of automatic engagement and affect recognition. Furthermore, this work is modular, making it extendible and transferable into other areas of HRI and affective computing.

V. Conclusion

Operating in alliance with a larger project with aims to develop a new generation of robotic tutors, the work detailed in this paper is realistic, achievable and pushes the boundaries of what is already possible. With access to several highly skilled and acclaimed partnering teams, this project benefits from the technical, psychological and pedagogical knowledge and experience required to forward the current state-of-the-art in engagement recognition.

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