Spotting social interaction by using the robot energy consumption

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Introduction

A study of long-term interaction with the robot embodiment of the companion called Sarah was conducted during the summer of 2012. The aim of the study was to see long-term implications when the robot embodiment was in a natural setting.

The robot interacted with 5 participants for 3 weeks in a office environment running continuously. Analysis of such a longterm experiment is a big challenge. Current robotics research has mostly addressed long-term interaction as a repeated interaction on a fixed task (e.g.(Leite et al. 2012)), but here we investigated a continuous interaction of 3 weeks.

The challenge is not only to evaluate the model implemented on the robot, but also the resulting behaviour of the robot. A method to evaluate the resulting behaviour is to evaluate the loop between human and robot. Hence, the idea is to evaluate the interplay presented in the interaction of human and robot (e.g (Lohan et al. 2012)).

The embodiment of a system like a robot in social situations is defined as not only dependent on its own sensory-motor experiences and capabilities but also on the environmental changes, caused by social constraints (Dautenhahn, Ogden, and Quick 2002). Thus, moving robots into social environments needs to be able to take their surroundings and the rules given by these surroundings into account. This is why from a robotic perspective, the interplay between its behaviour and the behaviour of its interaction partner(s), needs to be considered carefully.

Long-term social interaction between robot and human(s) creates very complex evaluation issues. Methodologies used in developmental psychology suggests that it is difficult to create a quantitative strategy to evaluate the long-term evolution of interactions. Hence, most research uses a sampling procedure, i.e. a experience-sampling procedure (Steiger et al. 1999).

A further problem that needs to be addressed in evaluating long-term interactions is one of big-heterogeneous data that results from it. This dataset comprises both video capture and system log files. To scale down the search space in the data, key-points in the interaction must be identified. Therefore, in this paper we consider the use of energy consumption of the robot to predict these key-points.

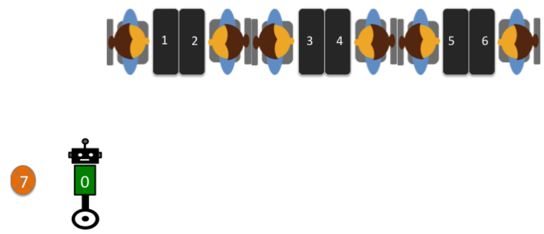

Figure 1: Label 1-6 workspace equipped with desktop computers, label 0 home position of the robot Sarah, label 7 charging station for Sarah

Long-term experiment

Five people voluntarily worked from the same office for three weeks came together with the robot Sarah. The participants carried out their normal everyday work and came from various other offices in the same building.

Setup

The open workspace the experiment was conducted in had 6 workplaces (see Fig. 1 label 1-6), at maximum of 5 participants were present at any one time. The spare desk was used for the experimenter if needed (e.g. if the robot needed service). All workplaces were equipped with a desktop computer and a webcam. The robot was capable of navigating to all workplaces (see Fig. 1 label 1-6), to its home position (see Fig. 1 label 0) and to its charging station (see Fig. 1 label 7), which it would seek autonomously when its energy became low (Deshmukh et al. 2011).

Sarah' Capabilities

Sarah was able to deliver messages left by visitors to the participants, navigate to their workspace autonomously and engage in a limited social interaction by asking preprogrammed questions (these questions changed every day). She was able to recharge her battery if necessary.

Participants

The five people voluntarily worked from the same office for three weeks. The recruited participants were two females and three males aged 51, 40, 26, 22, 28 and all employed

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in at the university. Office hours varied between the participants but they were present in the office between 3-5 days a week.

Data acquired

Resulting from these 3 weeks we collected system log files from Sarah. They contain amongst other information, Sarah's time based power usage, distance travelled, CPU usage of the laptop controlling Sarah, current usage of energy by the laptop, the current usage of energy by the platform and the voltage of the battery at any given time. In addition, the messages delivered and the task Sarah fulfilled were logged. Furthermore, video data was captured from a webcam mounted on Sarah and a camera placed on the ceiling of the office. Both cameras only recorded when motion was detected in the their field of view. Finally, skype interviews took place during and after the experiment, to pinpoint any interesting events.

Analysis

As stated above we start our evaluation on this huge data corpus by pinpointing key-points in the data stream. Therefore, we located one important social event described in the skype interviews as a referencing point, which should be picked up from our search. In this event the participants created a new task for Sarah by delivering cookies to all partner participants. Therefore, the participant placed a tray of cookies on Sarah and send to all her colleagues a message: "Help yourself to a cookie!". This new task occurs on day 4 in our experiment.

After defining this as an important social interaction, we created the hypothesis:

If Sarah was involved in more social interactions she used more power and therefore her total usage of power during a day would be higher then on the days when she was less involved with social interaction.

Thus, we analysed the system log files –compressing the information about Sarah's time power usage, distance travelled, CPU used on the laptop, the current used energy required by the laptop, the current use of energy required by the platform and the current state of voltage in the battery– to verify if there are correlations between the travels distance and the used power (see Fig. 2).

Results

Pearson correlation $(r(15640) = -.195, p <= .00001)$,is significant between the traveled distance and the used voltage. All other correlations are significant as well. Therefore, the distance travelled by Sarah and the current voltage of the battery is correlated to the amount of tasks she has fulfilled. When looking into the details of the voltage used from Sarah during the 3 weeks period, the local minima are highly interesting as these are the points in time Sarah were busy fulfilling tasks (see Fig. 3(1)). Hence, the number of local minima per day will give an insight in the overall usage of Sarah in each day (see Fig. 3(2)).

Finally, if we examine the local maxima presented in Fig. 3(2), we see a peak at day 4 at the time period when our participant induced the cookie task for Sarah.

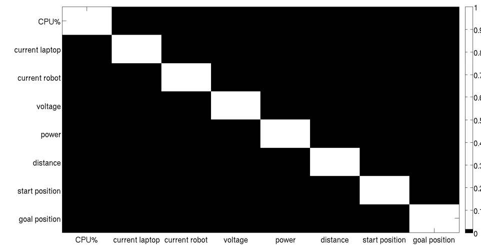

Figure 2: P-value of Pearson correlation.

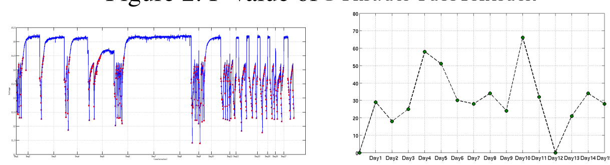

Figure 3: (1)Locale minima in used voltage with a minimal diastase of 10 minutes.(2) Number of social interaction Sarah was involved during the 3 week period, based on local minima in used voltage with a minimal diastase of 10 minutes.

Discussion

Lemaignan et al. have proposed a new model to investigate the cognitive correlation induced by a sustained human-robot interaction to measure anthropomorphism in human-robot interaction (Lemaignan et al. 2014). In this model the dynamics of anthropomorphism are distinguished by three main phases: *initialisation*, *familiarisation* and *stabilisation*, preceded by a pre-interaction phase. In the pre-interaction phase, users build an *initial capital of anthropomorphism (ICA)*. Once the interaction starts, the level of anthropomorphism increases due to the novelty effect, and then decreases to reach a *stabilised level of anthropomorphism (SLA)*. During the interaction, unpredicted behaviours of the robot (disruptive behaviours) may lead to local increase of the level of anthropomorphism.

Keeping this in mind, the number of social interaction Sarah was involved in can be interpreted as the following, *Day 1 is the initialisation phase*, the *familiarisation phase could be Day 2 - 8* , with a user *induced disruption at day 4*, and seen as the final *stabilisation phase is not present* in our data; on the contrary we found another *disruption on Day 9 and 12*. Therefore, one could argue that 3 weeks to interact with a robot companion is not enough to stabilise a cognitive image of its capabilities.

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