Are you playing with me? On the importance of Detecting and Recovering Disengagement in Mild Dementia Patients playing Brain-Training Exercises

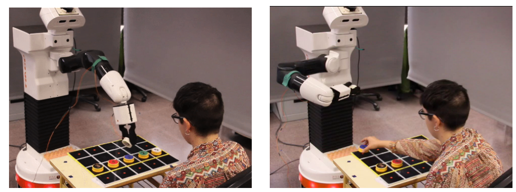
Antonio Andriella[1]

***Abstract*— The ability to automatically detect disengagement in a human-robot interaction can improve the overall quality of interaction in term of acceptance and effectiveness. Several cases of study have been conducted on this topic but none of them seems to be exploring how such application could benefit older adults with mental impairments. In this positional paper, we evaluate the benefit of combining two of the four Observational Measurement of Engagement(OME) indicators and contextual information to detect disengagement in older adults affected from Mild Dementia and Alzheimer playing a brain-training exercise. Moreover, we empower a robotic system of a repertory of re-focus strategies in order to re-engage the patient once a disengagement is detected.**

I. INTRODUCTION

In human-human interaction, engagement is defined as ”the process by which individuals in an interaction start, maintain and end their perceived connection to one another” [1]. Engaging older persons with dementia in appropriate activities has been shown to yield beneficial effects such as increasing positive emotions, improving activities of daily living (ADL) and improving the quality of their life [2]. Cognitive training is based on a set of standard exercises designed to reflect particular cognitive functions; usually the therapist sets different range of difficulty levels within the standard set of tasks to suit the individuals level of capability. In this work, we propose the Syndrom KurzTest (SKT). The SKT is a short test for assessing cognitive impairment of memory and attention [3].

One perspective to explore engagement in HRI is to investigate the automatic prediction of engagement. The main idea is to predict disengagement behaviors in real-time, so the robot can provide recovering mechanisms to keep the user engaged and eventually re-engage him. To this end, several solutions have been proposed combining different features. Castellano *et al.* [4] focus their work on collecting task-related features and social interaction cues trying to address the issue related to robustness in real-world scenarios. Nakano *et al.* [5] propose an engagement estimation method that detects the users disengagement gaze patterns. Rich *et al.* [6] develop and implement a computational model for recognizing engagement between a human and a robot. Szafir *et al.* [7] design adaptive agents that monitor student's attention in real time using measurements from electroencephalography (EEG).



(a) Robot provides help (b) User makes a move

Fig. 1: User is playing SKT with the robot's support.

The research on (dis)engagement detection has seen substantial advancements during the recent years. However there is still a considerable lack of experimental work focused on targeting persons affected by Mild Dementia and Alzheimer Disease. The study of how to automatically detect engagement is a necessary foundation for the development of non-pharmacological interventions for individuals with dementia, whether the interventions address depression or boredom. In the proposed scenario, we assume that the disengagement can be caused by the patient's lack of interest or negative attitude toward the task. The detection of disengagement of persons with dementia is expected to help such persons by increasing interest and his overall positive attitude.

In this positional paper, we attempt to fill the current gap by proposing a possible method aimed to potentially detect disengagement with older mentally impaired adults through a brain-training exercise. Our approach is based on the Observational Measurement of Engagement(OME) indicators, which were developed to specifically assess, within a certain subject, each level of engagement: attention, attitude, duration and refusal [8].

II. BRAIN-TRAINING EXERCISE SCENARIO

In this work we present a brain-training exercise based on a subset of the SKT. The goal of the test is to sort *n* tokens in ascending order on the board as quickly as possible and with the minimum amount of mistakes. An embodied robotic system, employed by a caregiver, is able to provide several levels of assistance on the base of the user performance and the state of the game combining different interaction modalities (speech and/or gesture). The assistance levels, as defined in [9] are:

*This work has received funding from the European Unions Horizon 2020 research and innovation programme under the Marie Skodowska-Curie grant agreement No 721619 for the SOCRATES project.

[1]A. Andriella is with Institut de Robòtica i Informàtica Industrial, CISC-UPC, C/Llorens i Artigas 4-6, 08028 Barcelona, Spain. aandriella@iri.upc.edu

- encouragement, in which the robot encourages the user to move a token;
- suggest subset, in which robot tells and points in the area of the solution;
- suggest solution, in which the robot tells and points the correct token;
- offer correct token, in which the robot gives the correct token to the user.

Figure 1 shows an example of interaction between the robot and the user.

III. SUGGESTED METHOD

A. OME Indicators and Contextual Information

We propose an extension to our previous work [10] adding a Disengagement Module which will be able to assess patient's disengagement based on OME indicators and contextual information. We decide to use only attention and attitude since we believe they are the most effective in this specific scenario. We define a stimulus as one of the assistance levels provided by the robot as defined in [9]. Each indicator is defined on a four-point scale: i) not attentive, ii) somewhat attentive, iii) attentive, and iv) very attentive. The specific outcome variables of the OME are defined as follows:

*a) **Attention**:* It is computed as the amount of time a participant looks at the robot and the board during the stimulus. The measurement starts as soon as the robot engages the user. To track the user's gaze we decide to use OpenFace [1]. We can define the percentage of time spent by the user focusing on the stimulus as:

$$attention = (T_b + T_r) * (100)/(Tot_{stim}) \tag{1}$$

where T_b is the time spent from the user on the board and T_r is the time spent by the user looking at the robot. Tot_{stim} is the total time of the stimulus (T_b+T_r<=Tot_{stim}). The outcome of this measure will be mapped on the four-point scale defined before.

*b) **Attitude**:* It is measured observing the user non-verbal expressions and it can be computed based on the concept of valence. To compute this value, we use Affectiva [2]. Here the valence metric likelihood is calculated based on a set of observed facial expressions [3]. We can define attitude as follows:

$$attitude = \arg\max_{i=1}^{4} \{perc\_attitude\_scale_i\} \tag{2}$$

where $perc\_attitude\_scale_i$ is the percentage of time the valence is on a defined point scale. At the end of an assistive action (stimulus) of the robot, one of the four point-scale is selected according to Eq. 2.

In this specific scenario is a primary aim of the robot to keep the user engaged in providing him with enough assistance in order to complete the game. Increasing the level of assistance could result in a loss of engagement by the patient since the task will be performed almost entirely by the robot. On the other hand, the selection of a lower level of interaction may result in insufficient assistance by the robot. This could mean the patient feeling frustration for not having achieved the goal or discouragement for having spent too much time to complete it.

We expect that the users engagement with the robot is both influenced by the task the user has to accomplish and the interaction with the robot. Moreover, we also expect that the different levels of assistance provided by the robot affect the different user's behaviors. For this reason, we include also the contextual information in the form of user performance as a parameter for deciding which action to perform in order to re-engage the user as soon as a disengagement is detected.

In particular we define the user performance in state s after an action of engagement e provided by the robot as:

$$user\_perf(e, s) = user\_move(e, s) * game\_diff(s) \tag{3}$$

where $game\_diff(s)$ is the current game difficulty in state s (computed based on the current state of the game and the user cognitive impairment) and $user\_move(e, s)$ is the outcome of the performed user move after an action of engagement e in state s. In other words, the harder is the game and the lesser is the level of assistance provided, the bigger will be the $user\_perf(e, s)$ value.

B. Disengagement Re-focus Stategies

The disengagement module for each state s computes a value defined as follows:

$$(dis)eng(s) = \alpha * attitude(s) + \beta * attention(s) \tag{4}$$

where α and β are weights for the two indicators. Those weights are important for analyzing the effect of each parameter separately and try to fine-tune the behavior of the developed module. Additionally, some studies point out how the effect related to ageing can affect the intentional display of facial emotions and the possibility of detecting unintended emotions [11]. So attitude, that is based on valence, can be ambiguous.

If a disengagement is detected, the robot based on the $user\_perf(e, s)$ value will evaluate which action to perform. To this end, it has been empowered with a repertoire of re-focus strategies in order to re-engage the user. The robot can:

- analyze the current user behavior and provide a more tailored support based on the current user performance (accuracy) and the time to perform the correct move (efficiency)
- re-engage the user providing the same assistance but with different modalities (using only speech or combining speech and gestures)
- alert the caregiver of the user's behavior asking him to intervene.

The module will provide at the end of the test session an accurate report of the user's total reaction time and number of mistakes.

[1] https://github.com/TadasBaltrusaitis/OpenFace
[2] https://www.affectiva.com/
[3] https://developer.affectiva.com/metrics/

IV. CONCLUSIONS

In this position paper, we evaluate the benefit to use a Disengagement Module in a brain-training exercise in order to detect people lack of attention and attitude toward the task. Combining user gaze direction, non-verbal features and contextual information, a robotic system will be able to evaluate the patient (dis)engagement and if it will deem it appropriate, it will try to re-engage it through a repertory of re-focus strategies.

As future work, we plan to validate the module in a real scenario. The main objective will be to evaluate the contribution of all OME indicators in the detection through questionnaires and videos analysis.

REFERENCES

[1] C. L. Sidner, C. Lee, C. D. Kidd, N. Lesh, and C. Rich, "Explorations in engagement for humans and robots," *Artificial Intelligence*, vol. 166, no. 1-2, pp. 140–164, 2005.

[2] K. K. Engelman, D. E. Altus, and R. M. Mathews, "Increasing engagement in daily activities by older adults with dementia," *Journal of Applied Behavior Analysis*, vol. 32, no. 1, pp. 107–110, 1999.

[3] J. E. Overall and R. Schaltenbrand, "The SKT neuropsychological test battery," *Journal of Geriatric Psychiatry Neurology*, vol. 5, no. 0891-9887, pp. 220–227, 1992.

[4] G. Castellano, A. Pereira, I. Leite, A. Paiva, and P. W. Mcowan, "Detecting User Engagement with a Robot Companion Using Task and Social Interaction-based Features Interaction scenario," *Proceedings of the 2009 International Conference on Multimodal Interfaces*, pp. 119–125, 2009.

[5] Y. I. Nakano and R. Ishii, "Estimating user's engagement from eye-gaze behaviors in human-agent conversations," in *Proceedings of the 15th International Conference on Intelligent User Interfaces - IUI '10*. New York, New York, USA: ACM Press, 2010, p. 139.

[6] C. Rich, B. Ponsler, A. Holroyd, and C. L. Sidner, "Recognizing engagement in human-robot interaction," *2010 5th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pp. 375–382, 2010.

[7] D. Szafir and B. Mutlu, "Pay attention!: designing adaptive agents that monitor and improve user engagement," *Proceedings of the 2012 ACM Annual Conference on Human Factors in Computing Systems - CHI '12*, pp. 11–20, 2012.

[8] J. Cohen-Mansfield, M. Dakheel-Ali, and M. S. Marx, "Engagement in persons with dementia: the concept and its measurement," vol. 6, no. 4, pp. 247–253, 2009.

[9] A. Andriella, G. Alenyà, J. Hernández-Farigola, and C. Torras, "Deciding the different robot roles for patient cognitive training," *International Journal of Human Computer Studies*, vol. 117, pp. 20–29, 3 2018.

[10] A. Andriella, G. Alenyà, and C. Torras, "Cognitive System Framework for Brain-Training Exercise based on Human-Robot Interaction," *Submitted for publication*, 2018.

[11] N. C. Ebner, Y. He, and M. K. Johnson, "Age and Emotion Affect How We Look at a Face: Visual Scan Patterns Differ for Own-Age versus Other-Age Emotional Faces," vol. 25, no. 6, pp. 983–997, 2012.