Engineering Applications of Artificial Intelligence 56 (2016) 185–199

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Validation of the reasoning of an entry-level cyber-physical stroke rehabilitation system equipped with engagement enhancing capabilities

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ARTICLE INFO

Article history:
Received 23 January 2016
Received in revised form
3 August 2016
Accepted 13 September 2016

Keywords:
Cyber-physical stroke rehabilitation system
Engagement enhancing
Reasoning in context
Stimulation strategy
Learning mechanism
Accuracy of suggestions

ABSTRACT

Maintaining and enhancing engagement of patients during stroke rehabilitation exercises are in the focus of current research. In the preceding phase of our research, an entry-level cyber-physical stroke rehabilitation system (CP-SRS) has been developed, with the aim of enhancing patients' overall engagement during rehabilitation exercises. As a follow up on the evaluation of the proposed engagement enhancing method and the smart learning mechanism based on the simulated data, this paper presents the validation results of the proposed CP-SRS system based on real-life data. Validation included two aspects: (i) validation of the effectiveness of the applied stimulation strategies (SSs), and (ii) validation of the accuracy of the suggestions of the smart learning mechanism. Methodologically, a within-subject experiment was designed and completed. Eighteen subjects were recruited to participate in the experiments, based on convenience sampling. During the completed game exercises SSs were applied individually as well as in combination. The engagement levels of the participants were evaluated and recorded after applying the SSs individually and combined. The results were processed by within-subject ANOVA in order to test if there was a significant difference between the influences of the different SSs and combinations. In addition, training and testing of the smart learning mechanism (SLM) was also executed in MATLAB. The results indicated that several SSs significantly increased the engagement of the subjects, and that both neural network-based SLM and the Naive Bayes-based SLM were able to learn and discriminate the effects of the various SSs. Our conclusion is that they both can be used to assist making decision on effective application of SSs. However, applying neural network-based SLM is more appropriate in the context of increasing engagement.

1. Introduction

1.1. Concept of therapeutic engagement

Engagement in rehabilitation appears to be much more than just a patient attending a therapy. Although stroke patients are supposed to proactively and intensively participate in the rehabilitation program and therapy exercises, it does not mean that they are actually always engaged. In fact, various models have been proposed to capture the essence of engagement from various fields, such as (i) flow theory-based model (Csikszentmihalyi and Csikszentmihalyi, 1988), (ii) model of technology application raised engagement (O'Brien and Toms, 2008), (iii) model of social engagement (Martin and Osberg, 2007), (iv) model of education engagement (Kuh, 2003), and (v) model of therapeutic engagement (Lequerica and Kortte, 2010). The engagement models proposed by researchers of different knowledge domains aimed at understanding and representing engagement from different perspectives. To set up their models, they have identified a wide range of substantial influencing factors. Many of them are used in more than one model, therefore they can be considered as common influencing factors of the phenomenon of engagement, such as: (i) understanding the goal of the tasks/activities, (ii) taking challenge, and (iii) handling circumstantial elements (settings of activities, aesthetics of the environment, feedback, and control).

Engagement is a complex construct, which also depends on the context. In the context of rehabilitation exercises, engagement has been defined as a construct that is driven by motivation and executed through active and effortful participation (Lequerica and Kortte, 2010). Lequerica and Kortte proposed the components influencing therapeutic engagement includes (1) perceived need of

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http://dx.doi.org/10.1016/j.engappai.2016.09.006
0952-1976/

treatment, (2) perceived likelihood of a successful outcome, (3) perceived self-efficacy to complete the tasks, and (4) reassessment of beliefs, attitudes, &expectations. Kortte et al. developed an engagement rating scale, which took rehabilitation engagement, therapy absences, functional status, emotional functioning, affective state, level of functioning and denial into consideration (Kortte et al., 2007). By studying the engagement models and the context of rehabilitation, we sorted the influencing factors into four distinct sets of human-related factors. These sets include: (i) motor, (ii) perceptive, (iii) cognitive, and (iv) emotional factors, respectively. For each of these engagement influencing factors a formal definition will be given in the next section.

A major issue (and limitation) is that the currently available methods of evaluating and measuring engagement are subjective and qualitative. This can partially be explained by the nature of engagement. The engagement of the same patient can be different according to the different approaches of therapists, which may also lead to an inaccurate assessment of the engagement level. Evidentially, the methods of engaging the user cannot be validated without precise measurement. The trend in rehabilitation robotics is to develop robotic systems, which can provide direct quantitative feedback to the patient about her/his performance during the therapy, and this way can enhance the personal motivation and the self-appraisal of the value of the proposed exercises (Garcia et al., 2011). In education, several studies have been conducted with the objective to evaluated student's engagement based on postures (D'Mello et al., 2007; Sanghvi et al., 2011), body motion (Sanghvi et al., 2011), or log files in e-learning system (Cocea and Weibelzahl, 2007). Szafir and Mutlu (2012) developed an adaptive agent that monitors the cognitive engagement of students and improves their engagement during learning. They used electroencephalography (EEG) to quantitatively represent the engagement level of students. An adaptive agent, implemented as a robotic instructor, was used to monitor the engagement levels based on EEG. The agent was capable to give immediacy cues and triggered regaining the participant's attention by drops. Although this method seems to be promising in education, a more comprehensive characterization of the engagement is needed in the context of rehabilitation training integrated with video games. It is important to monitor not only the cognitive engagement of patients, but also their motor, emotional and perceptive engagement, considering all influencing factors of therapeutic engagement.

1.2. State of the art of engagement enhancing methods

It has been demonstrated that engagement can remarkably improve the functional outcome of technology-assisted stroke rehabilitation (e.g., Prange et al. (2006), Henderson et al. (2007) and Kwakkel et al. (2008)). Furthermore, the recent research results suggest that active participation in rehabilitation promotes cortical plasticity, which may lead to restoring motor abilities (Fiedler et al., 2000; Lynskey et al., 2008). There have been various methods and computer supported tools developed in order to avoid mundane exercising, that is prone to become a routine, or even boring for the patients, and leads to ineffective training. The most common computer supported methods include: (i) assist-as-needed algorithms (to provide the minimal robotic assistance for the patient to complete a motion), (ii) detection of patient intent to move, and (iii) virtual reality games for a more immersive experience (Blank et al., 2014).

With the goal of facilitating motivation, guidance and encouragement, VR-based solutions aim at augmenting the information gained by intrinsic sensory organs (Holden, 2005). Interactive environments have been used to encourage sensory-motor integration by providing feedback relevant to a specific function through various modalities, and by presenting this information in a meaningful and intuitive way (Sveistrup, 2004). It has been found that the task and feedback should encourage active physical and cognitive participation of the patients in learning generalizable movement strategies (Schmidt, 1991). The task and feedback must be adaptable to the patient's individual ability and progress, allowing for patients to be challenged physically and cognitively without frustrating them (Piron et al., 2005). As argued by Adamovich et al. (2005), measuring the activities has an important role. VR-based rehabilitation systems offer numerous advantages. On the other hand, they also have weaknesses and limitations such as: (i) challenging user interface and interaction methods, (ii) using instruments, displays and wiring, (iii) immature engineering processes, (iv) platform compatibility and interoperability, (v) front-end flexibility, (vi) back-end data extraction, management, analysis, and (vii) visualization side effects (Kim et al., 2015).

Assist-as-need algorithms and detection of patient intent to move can be seen as methods of providing personalized treatment. Personalization is an elementary need in recommendation oriented rehabilitation systems. Recently, there have been various computer supported tools developed for personalized rehabilitation. Most of these tools can set the difficulty of the training exercise according to the capability of the patients, or customize the difficulty level of the training exercise or the game according to the performance of the patients (Ding et al., 2013; Pastor, et al., 2012). Few studies have been conducted to address personalized treatment in cognitive, perceptive, and emotional aspects of engagement. Alankus et al. (2010) developed customizable games for stroke rehabilitation, in which cognitive and motor challenges could be adjusted by physical therapists. They found in a case study that a stroke patient recovered significant motor abilities by training with customizable games over six weeks. This system implemented personalization in the cognitive aspects of rehabilitation, and this has been shown to be beneficial even for the motor recovery. These researchers did not evaluate the patient's engagement in the study. Tam et al. (2003) developed a telecognitive rehabilitation program, which could be customized according to the patient's functional levels and living environment. Specifically, the software could customize the immediate visual and auditory feedback and could provide personalized feedback to motivate the client. The three persons with brain injury showed improving trends and levels of specific cognitive performance during the treatment. Thought the system was able to customize the perceptive feedback, the study did not demonstrate if this customization could actually enhance the patient's engagement.

In the last years, machine learning technology has been used to provide personalized training for patients. Shirzad and Van der Loos (2013) compared the performance of three machine learning algorithms in predicting a user's desirable difficulty based on the user's motor performance and physiological signals (i.e. skin temperature, respiration rate, and skin conductance rate) during a reaching motion task. They found that a neural network approach gives higher prediction accuracy in comparison with models based on k-nearest neighbor and discriminant analysis. However, they did not consider cognitive and emotional aspects of user engagement since the task to be completed was only a reaching motion task (rather than a task that would have involved gamification). Chanel et al. (2011) explored the opportunity of using EEG or peripheral signals (i.e. galvanic skin response, heart rate, skin temperature, etc.) to classify anxiety, engagement, and boredom states when the user was playing a Tetris game with different difficulty levels. They found that EEG provided a better accuracy in classification than the peripheral signals. Researchers have also explored providing personalized training using patient's success rate in game tasks (Borghese et al., 2013) and physiological reactions in virtual reality system (Badesa et al., 2014).