Gesture Therapy 2.0: Adapting the rehabilitation therapy to the patient progress

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Abstract. Gesture Therapy is a low–cost, virtual reality based therapy to aid stroke patients to recover upper–limbs' motor skills by playing videogames that re–create daily–life activities. In this paper, we extend our previous work on Gesture Therapy to adjust the difficulty of the game accordingly to the performance of the user. A partially observable Markov decision process is used to adapt the difficulty level from speed and deviation from smooth motion paths. In addition, we consider recently proposed criteria such as *motivation*, *adaptation*, and *task repetition* to design our rehabilitation games. Preliminary results show that the system is able to identify the user dexterity and adjust the difficulty level accordingly. We believe that, in the future, the adaptation module will strongly contribute to relocate therapy sessions from rehabilitation centers to home, and also to decrease the need for on–site assistance of professional therapists.

1 Introduction

In 2010, the American Heart Association –*AHA*– and the National Institutes of Health –*NIH*– branded stroke as the leading cause of motor and cognitive disabilities in the world requiring rehabilitation therapy [1]. Unfortunately, the high cost of therapies [2] makes them prohibitive for many people, especially in middle and low income countries. In a previous work [3] we described the Gesture Therapy system –*GT*– that is a low–cost therapy system that combines computer vision and virtual reality –*VR*– in which patients recover while they play short games that simulate daily–life activities. Initial clinical evaluations [4] suggest that GT can compete with more classical occupational therapies in terms of motor skill recovery and confirms the suspected extra motivation evoked in the patients.

In this paper, we present an extension to the GT platform that incorporates an adaptation module aimed to maintain a suitable level of difficulty of the game accordingly to the user performance. A partially observable Markov decision process –*POMDP*– was designed to infer the patient status from simple motion features such as speed and deviation from smooth motion paths. The action policy generated from the POMDP is able to ease the difficulty level of the game if the performance of the patient decreases, it hardens the game as the user motricity improves, or maintain the difficulty level if no change is observed. In contrast to commercial games in which the difficulty is always increased through the game, GT 2.0 adapts to the patient needs in real–time. Moreover, we argue that our approach fulfill recently proposed criteria to design rehabilitation games such as user motivational feedback, adaptation to motor skill level, task repetition, and simple objective achievement. An initial evaluation shows the reliability of the overall approach, the suitability of the system to identify the user dexterity and to adapt the difficulty of the game accordingly. We believe that, in the future, GT 2.0 will effectively contribute to move therapy sessions from stroke rehabilitation units to home, and to reduce the need for continuous evaluation and assistance of physical therapists.

The outline of this document is as follows. Section 2 discusses related work on recent alternatives to rehabilitation therapy. In Section 3, the general architecture of our system is described. Section 4 presents the POMDP–based adaptation module. Section 5 describes our experiments and results. Finally, section 6 draws our conclusions and future work.

2 Related work

Literature shows several different alternatives to aid patients to improve motor skills and functions of upper–limbs after stroke. Common rehabilitation treatments –or interventions– includes mental practice, neurophysiological approaches, and repetitive task training [5]. Recently, encouraging initial results obtained from computer–based assistive technology such as robotics and VR games have shown the effectiveness and flexibility of these interfaces to aid patients in their rehabilitation process [6–8]. In particular, virtual reality based interventions represent a more affordable option to other therapy alternatives, without compromising the restoration of motor skills. Furthermore, it allows for fast prototyping and development, wide acceptance, and personal customization added to an edge in evoking motivation from the patients [9]. It has been shown that probabilistic–graphical models such as Bayesian networks and POMDPs provide a suitable framework to generate advice to patients and adjust the therapy accordingly to their requirements [10, 11]. In particular, POMDPs account for noisy observations from the world, uncertainty in the current state of the process and its transitions to other states, while computing a mapping from belief states to actions –also called a *policy* [12]. These are desirable features to be considered when observing and modelling the activity of post stroke patients; for example, in the presence of either motion capture sensors with limited perceptual capabilities or partial descriptions about the current internal state of the patient. These situations may produce non accurate observations of the performance of the user in the game.

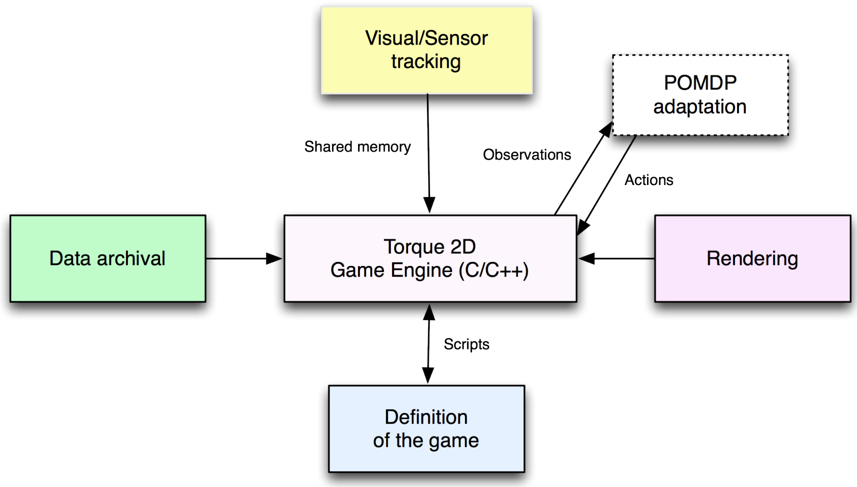

Fig. 1. Schematic representation of the Gesture Therapy 2.0 architecture.

Recently, and closely related to our proposal, Goetschalckx *et al.* [19] described a POMDP–based approach to adjust the difficulty level of a rehabilitation game using a robotic device as the input inteface. However, definite probabilistic models for achieving this goal are far from being fully developed, and new model and interface proposals are needed to be explored, for example, to combine personal adaptation and motivation information to produce an integral and confortable experience for the patient. The present document is a contribution to solve this problem.

3 Architecture of GT 2.0

The GT 2.0 platform is depicted in Figure 1. The central axis of the platform is built around Torque 2D –*T2D*– that it is an commercial engine for rapid game prototyping. T2D centralises communication among all other modules. The module named *Definition of the game* communicates with the T2D by means of control scripts. The *Data archival* module is a database managing system –*DBMS*– for storing patient movements. *Visual/Sensor tracking* module generates visual and gripper data that are accessed by T2D via *shared memory*. The *Rendering* module provides visual feedback to the user accordingly to its performance. As the user interacts with the system, GT 2.0 stores patient movements in the data archival and transmit these to the game, which responds to the user input and further provides observable data to the adaptive module. Figure 2 shows an example of a real user interacting with the system in a kitchen environment.

Fig. 2. Example of a real user interacting with the system that re–create a kitchen environment.

Finally, the *POMDP adaptation* module is responsible for changing the difficult level for the game. This module is described in the following section.

4 POMDP adaptation module

As stated above, the GT adaptation module is implemented using a POMDP. The POMDP framework is used to quantify the "convenience" of the states of a system although its real situation is not completely known, and hence, to plan optimal actions to reach a goal state. A POMDP is a tuple

$$POMDP =< S, A, O, R, \Omega, T, I >$$

where S is a set of states, A is a set of actions, O is a set of observations, R is a reward function of executing action $a \in A$ when in state $s_t \in S$ and moving to state $s_{t+1} \in S$; T represents the transition probability ditribution among states and an action, Ω describes the conditional observation probabilities at each state in S, and finally, I is the initial state probability distribution. Needless to say, a POMDP is one that complies with the Markovian property. A Bayesian graphical representation of a POMDP is illustrated in Figure 3.

Our POMDP implementation is built upon symbolic–Perseus algorithm and software [13] that allow factored representations of state and observation variables. Initially, the POMDP of the GT adaptive module considers two hidden –or state– variables named *Performance* of the user and *Difficulty* of the game;

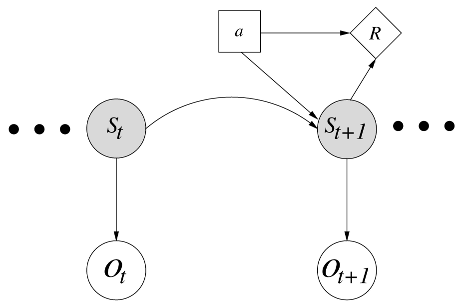

Fig. 3. A Bayesian network description of a POMDP unrolled two times from t to $t+1$, with an action a and a reward function R. Shaded circles indicate state variables S_t and S_{t+1}; white circles are observation variables O_t and $O_t + 1$.

and two observable streams *Control* and *Speed*, as shown in Figure 4. Control is determined as the deviation in the trajectory from a straight movement from origin –cursor position at the instant of target popping– and target location. The more deviation from this straight path, the less control. Control is considered in 3 ranges; low –*coff*–, normal –*cb*– and good –*con*. Speed corresponds to the ratio of distance along the optimum path and execution time. Similarly to control, speed is also considered in 3 ranges; low –*soff*– , normal –*sb*– and good –*son*. The combination of control and speed dictates the performance of the user –*bad*, *good*, and *outstanding*– in turn governing the game difficulty. The variable Difficulty can take three possible values: *easy*, *medium*, and *hard*. We consider three possible actions: *dolvlup*, *dolvldown* and *do_nothing* that increases, decreases and keep unchanged the difficulty of the game, respectively. Decisions are made in order to keep the difficulty level in balance with respect to the performance level –i.e., Performance=bad and Difficulty=easy, Performance=good and Difficulty=medium, or Performance=outstanding and Difficulty=hard. For example, if the user performance is outstanding and the game difficulty is easy, the POMDP action policy increases the difficulty of the exercise to medium; if the user continues its excellent performance, the module then increases the game level to hard. Decisions to decrease the difficulty level are made at any moment the performance is below the current difficulty level. Decision to do nothing takes place whenever the performance level is balanced with respect to the difficulty level. Positive rewards are assigned in this latter case only.

5 Experiments and results

In this section, we present a preliminary round of tests performed to evaluate the overall functionality of our proposal and its results. First we discuss design criteria we follow in order to construct our rehabilitation game.

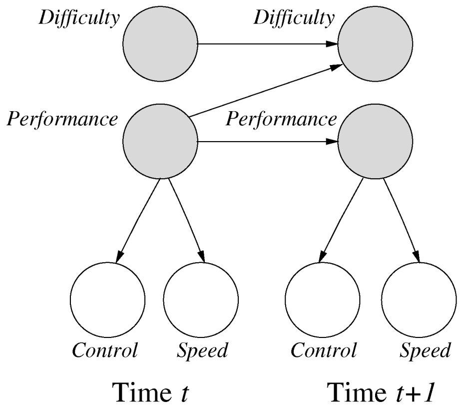

Fig. 4. The GT adaptive module POMDP.

5.1 Design criteria for rehabilitation games

Without detracting of the traditional criteria of repetition and meaning in rehabilitation therapies, the new generation of therapies emphasizes motivation trying to avoid boredom in the therapeutic sessions [8]. Higer motivation by patients often turns into higher commitment thus facilitating recuperation. Serious games used in the motor rehabilitation by means of virtual reality based therapies should provide a safe, adequate and attractive environment to patient [8]. In developing these games not only classical aspects present in leisure games such as temporality, sound, graphics, step or learning curve among other must be cared for. In addition, rehabilitation serious games must also incorporate criteria and objectives specific to rehabilitation of patients with motor impairment. Here, in Table 1 we give a naive classification of a few of these rehabilitation intrinsic criteria. Primary criteria correspond to the elements that ought to be present in any rehabilitation therapy. Secondary criteria agglutinates those criteria desirable to be incorporated in the rehablitation games. Finally, because the population affected by stroke has a certain profile [1], it is not surprising that these games incorporate elements of entertainment focused to objective population, some of which are covered in Table 1. The table does not aim to be exhaustive and for instance does not include clinical parameters such as timing or dose, the initial state of the patient represented by its age, presence of depression, health and lifestyle or support network, as it does not include particularities of the motivation such as expectancy, self-efficacy, compliance and adherence, etc [5, 8, 14–18]. Yet those criteria indicated in Table 1 can be argued to be the most relevant permeating all other criteria.

To demonstrate the adaptive system a dummy game was created. Note that this game is not part of the GT platform itself as it lack some of the features indicated in Table 1. Nonetheless, the game incorporates the motion replay, and is arguably engaging. The types of movement covered are complex –the movement occurs along the two screen dimensions–, the platform automatically provides

Primary	Secondary	Social group specific
– Motion replay – Meaningful/Significative task – Motivation	– Type of movement covered –unidirectional, combined, complex– – Exhaustion/Fatigue level – Affective level – Reduction of compensation movements – Focus diverted from exercise – Simple interface and clear objective. – Therapy-appropriate range of movement – Adaptability to patient needs	**Elderly** – Control of frustration level – Attention level **Infants** – Educative – Language

Table 1. Summary of some important criteria for designing serious games focused in motor rehabilitation therapy, with exemplary criteria for social groups. This criteria as well as others not included here have been mentioned earlier in literature [5, 8, 14–18].

support for detecting compensation and the interface is clear and objective. The adaptability criteria is the one under development in this paper. The game presents a flying cooked steak and a cursor. The goal of the game is simply to cross the cursor over the flying steak as many times as possible and as fastly and accurately as possible, using the GT hand grip control. Everytime the heart of the steak is crossed with the cursor the steak randomly changes its location in the screen, with the new location only being allowed to be at a maximum distance from the cursor depending on the game level dictated by the adaptive system.

5.2 Evaluation and results

To test our approach we use a 2Gb 1.86GHz Dual–Core desktop computer. To capture images a cheap webcam was used. Image frame rate of the visual system is about 15 FPS with a resolution of 320×240 pixels. Experiments were performed in our lab environment with artificial light. The distance between the user and the videocamera is around 1m.

We conducted a preliminary set of experiments to evaluate the adaptation module response to modify the difficulty level of the game accordingly to the user performance. Four healthy subjects were recruited among the staff and students of the National Institute of Astrophysics, Optics and Electronics. Following a brief description of the system by the researcher the subjects were allowed to familiarise with the system for about 1 minute. Each session lasted 3 minutes aprox. corresponding to interleaved blocks of activity –1 minute each– and –rest 20 seconds each–, starting and finishing in activity.

Fig. 5. One of the subjects playing the adaptive game during the experiment.

A depiction of the experimental set up can be seen in Figure 5. As the system is prepared for people with motor disabilities, the healthy subjects can easily master the game and consequently reach the maximum level of the game within a very short amount of time. In this sense, the rest periods are aimed to allow the adaptive system to sense a "bad performance" and thus lower the game difficulty. After the session was finished, the log file was saved for offline analysis. Data from subject 3 was discarded as he deviated from the protocol.

Figure 6 illustrates the timecourse of the the observable variables –speed and control–, the action taken –action– and the output –level– for one of the subjects. From these results it emanates how the POMDP assesses the player ability status and determines in real-time whether to increase, decrease or leave unaffected the game difficulty. During the active periods the game through the POMDP and based on the observation of speed and control takes no action and maintain the level. A few seconds after entering the rest periods, and detecting no success in achieving the task as a result of lack of activity, the POMDP delivers a *dolvldown* action which the game translates to a decrease in the level. As the activity resumes, and the player hit the target in appropriate speed and control, the POMDP emit a *dolvlup* resulting in the increment in game level. Note how the system determines action to lower the difficulty during the rest periods for all subjects, even if not necessarily resetting to the easiest level. The module reaction in terms of increasing or decreasing game difficulty may be tuned according to the therapy requirements.

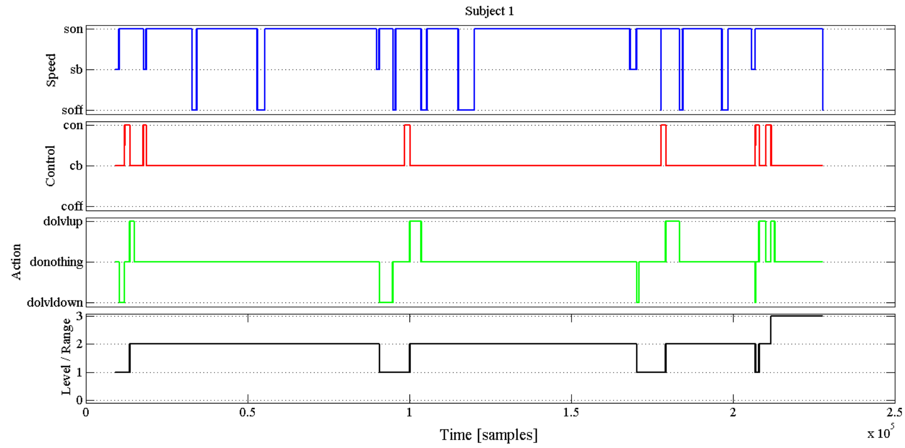

Fig. 6. Timecourse of the observable variables –speed and control–, the hidden variables –performance and difficulty–, the action taken –action– and the output –level– for subject 1. It is shown that the level of the game is modified accordingly to the values of speed and control observations. For example, whenever speed and control variables reflect a good performance –son and con, respectively– the adaptation module selects the action dolvlup, and the level of the game is increased.

6 Conclusions

In this paper we presented a new adaptation module for the GT rehabilitation platform. The system infers the user performance by observing its speed and control while it plays. Upon determining subject performance, the POMDP decides whether to increase or decrease game difficulty -or leave it unchanged-. We have shown preliminary results for healthy subjects. We intend to further analyse the system response in healthy subjects before carry on with rehabilitation patients. As new games are incorporated to the gesture therapy repository, it will be necessary to assess how the game meets the goals/objectives of a rehabilitation game.

In terms of the rehabilitation therapy, the new module provides a dynamic environment capable of tailoring behaviour to user progress. The importance of this is twofold; (i) the presence of therapist is not required continuously and (ii) the patient can now proceed with its rehabilitation at home at its own pace. This contribution to the rehabilitation therapy is expected to go hand in hand with an enhancement of the user experience. This is yet to be tested in a clinical evaluation but the hypothesis being that the patient will benefit from a self-pace progress resulting in an adequate patient specific cognitive, physiological and mechanical load reduction. Moreover, it is expected that the self-pace progress will increase compliance with the therapy, an especially critical point when therapy is to occur away from the therapist.

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