33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Adaptive Rehabilitation Gaming System: On-line individualization of stroke rehabilitation

Jens Nirme, Armin Duff and Paul F. M. J. Verschure

Abstract— **The effects of stroke differ considerably in degree and symptoms for different patients. It has been shown that specific, individualized and varied therapy favors recovery. The Rehabilitation Gaming System (RGS) is a Virtual Reality (VR) based rehabilitation system designed following these principles. We have developed two algorithms to control the level of task difficulty that a user of the RGS is exposed to, as well as providing controlled variation in the therapy. In this paper, we compare the two algorithms by running numerical simulations and a study with healthy subjects. We show that both algorithms allow for individualization of the challenge level of the task. Further, the results reveal that the algorithm that iteratively learns a user model for each subject also allows a high variation of the task.**

I. INTRODUCTION

STROKE represents one of the main causes of adult disability and will be one of the main contributors to the burden of disease in 2030 [1]. Following stroke, patients show a range of deficits, including motor deficits, sensory impairments, aphasia, spasticity, chronic pain, mood disorders and depression [2-6]. There is considerable variety in the treatment concepts and therapies that address stroke, without a clear consensus [7]. The efficacy of stroke therapy has been shown to depend on a number of parameters. First, treatment frequency and intensity has been shown to correlate with recovery [8-9]. Second, the specificity of rehabilitation training with respect to the deficits and required functional outcomes has an impact on recovery [10]. Indeed, specificity is also seen as a central concern in occupational therapy [11]. Third, it has been shown, that the configuration of the training and its variety has a direct influence on motor learning [12-13].

Recently, standard rehabilitation has been augmented with new interactive technology. In particular, the use of virtual reality (VR) systems allows higher levels of interaction as well as a greater variety of games and tasks. Most importantly, VR provides the users with a feedback on their success in completing the tasks within a game. Nevertheless, it must be emphasized that not much work exists on the quantitative assessment of the clinical impact of VR based-therapies and their effects on neural reorganization. In this context, the Rehabilitation Gaming System (RGS) is a noteworthy exception [14-15].

RGS is a VR based rehabilitation system that integrates a paradigm of action execution with motor imagery and action observation. In RGS, the movements of the arms are mapped to a virtual character via a tracking system, which includes a camera and colored patches that the users wear on their wrists and elbows. This is combined with a pair of data gloves to capture finger movements [14]. The hypothesis behind the choice to combine movement execution with the observation of correlated action of virtual limbs in a first-person perspective, is that within this specific scenario, recovery can be accelerated and enhanced by driving the so called mirror neuron system (MNS). The MNS can be seen as an interface between the neuronal substrates of visual perception and motor planning and execution [16]. The clinical trials that have been performed thus far show that RGS accelerates recovery of acute and chronic stroke patients as measured on the Chedoke Arm and Hand Activity Inventory. Remarkably, RGS has been proven to be as effective in recovery of movement speed as the intense and therapist dependent occupational therapy [14, 15].

As a rehabilitation and diagnostics technology RGS incorporates essential features of successful rehabilitation including task individualization and variation. One aspect of individualization is how and to what degree the users are challenged when using the system. It has been suggested that an intermediate level of arousal promotes optimal learning. If the challenge is too low the motivating potential of arousal is lost, and if the challenge is too high the users experience stress having a negative effect on learning performance [17]. This balance is considered a necessary condition for the sensation of *flow*, a concept describing a state of full involvement in an activity [18]. Variation in the game can be achieved by varying the configuration of the game maintaining the challenge for the user within the optimal range.

In RGS individualization and variation where attained by adapting the parameters of the game following a psychometric model that was estimated from a group of healthy subjects and from patients [14]. The psychometric

Manuscript received April 15, 2011. This work was supported in part by by the European Commission through the project Rehabilitation Gaming System - RGS [EC-FP7 Ambient Assisted Living Joint Programme, AAL-2008-1-119].

J. Nirme is with the Laboratory of Synthetic Perceptive Emotive and Cognitive Systems (SPECS), Department of Technology, Universitat Pompeu Fabra, 08018 Barcelona, Spain (e-mail: plustic@gmail.com).

A. Duff is with the Laboratory SPECS, Department of Technology, Universitat Pompeu Fabra, 08018 Barcelona, Spain (e-mail: armin.duff@upf.edu).

P.F.M.J. Verchure is with the SPECS, Department of Technology, Universitat Pompeu Fabra, 08018 Barcelona, Spain and Institució Catalana de Recerca i Estudis Avançats (ICREA), Barcelona, Spain (corresponding author phone: +34935422201; fax: +34935422202; e-mail: paul.verschure@upf.edu).

model maps the parameters of the game to the challenge level and thus is game specific and has to be estimated for each game from a representative group of users.

In order to individualize rehabilitation, it is indispensable to know the relation between the configuration of the therapy and the challenge level it represents for the patients. For the increasing number of new therapy procedures it seems an insuperable effort to estimate a psychometric model for each new therapy scenario. This paper investigates the possibilities to automatize this process. We propose two mechanisms to control configuration of rehabilitation tasks automatically. Using numerical simulations and a study with healthy subjects, we show that by applying the algorithms we can adapt the properties of the game to produce both optimal challenge levels and variation.

II. Methods

To substantiate the concepts of individualization we apply them to the spheroids game used in the current study as an example system. In this game, the users see approaching spheres with varying speed, interval and offset to the left or the right of the center. Their task is to touch the spheres with their left- or right hand respectively.

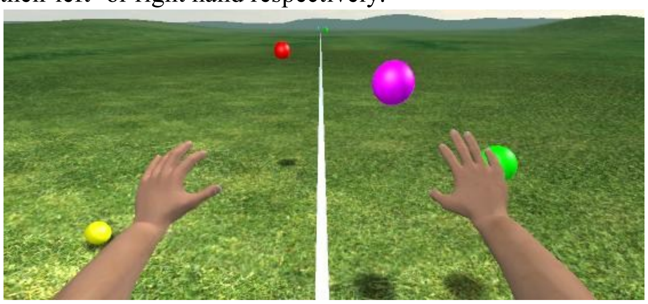

Fig. 1. Users view during the spheroids game. Spheres of variable sizes approach the virtual arms with variable velocities, at variable intervals and at different distances from the centerline.

The level of challenge of this task is controlled by the parameters *speed, range, size and interval*. The challenge is measured and controlled over the *performance* of the subjects, defined as the percentage of balls touched on either side. The game parameters are modified in such a way that the performance is close to the predefined *target performance*.

Speed is defined as the velocity at which the spheres travel. *Range* is the range from the center line at which the spheres can be launched (the positions for each ball is randomly selected within this range). *Size* represents the radius of the spheres. *Interval* is the time between the launch of two consecutive balls. From now on, we will refer to these parameters as difficulty parameters. The ranges of all difficulty parameters are scaled to the interval 0 (easiest) to 1 (most difficult). All the difficulty parameters, except interval, are separable between the left- and right side, allowing lateralized control of the challenge.

In this context, the aim is to change the difficulty parameters over a large range while maintaining an optimal challenge level, i.e. minimize the difference between the actual performance and the target performance.

A. Algorithms

To address the problem of controlling the degree and variation of the challenge in the games of the RGS, we developed two algorithms with distinct behaviors. The first algorithm is the *random-line-search*. The problem was cast as a local search in a search space defined by the ranges of the difficulty parameter. It's solved by an adaptation of a *random walk* algorithm modified to avoid getting stuck in local- or temporal optima[19]. The algorithm moves stepwise across the search space in a randomly selected direction until either the error of the resulting performance relative the target performance grows or changes sign (overshoots). The step size is modulated by the magnitude of the performance error.

The second algorithm is the *predictive-search*. It learns a function approximating the users' performance given a set of difficulty parameters, i.e. a user model [14]. It then uses this model to randomly select values of the difficulty parameter within the sub-space where the model predicts a performance close to the target performance. The user model has the form of a polynomial of constant, linear and interaction terms and is obtained and updated by online regression using a single layer perceptron network back propagating the prediction error (actual performance – predicted performance). The weights of the terms are updated by the delta rule with a linear activation function [20]. When the performance is outside a predefined range from the target performance the new difficulty parameter values are selected only within the negative or positive quadrant relative the current position in the search space, similar to the random-line-search algorithm.

Both algorithms update left and right difficulty parameters separately. Those parameters which are not separable (e.g. interval in the *Spheroids game*) are treated as a special case and selected taking into account the performances of both the left and right arm.

B. Simulations.

In order to assess the basic properties and differences of the two algorithms, we ran two sets of numerical simulations. In simulation 1 we want to identify good configurations of the algorithms and reveal overall performance of the algorithms. To do so we varied the step size function in the random-line-search and learning rate and range of performance error to allow unconstrained search in the predictive search algorithm. Performance resulting from set of difficulty parameter was estimated by the psychometric model used in RGS [14]. The psychometric model allows calculating the challenge given the difficulty parameters. In order to calculate the performance we define a parameterized function describing the relation difficulty-performance. We systematically added different levels of noise in order to estimate the stability of the algorithms.

In simulation 2 we assessed the stability of the algorithms in respect to the number of difficulty parameters. We randomly generated coefficients for constant, linear, interaction and quadratic terms for a polynomial function describing the relationship between difficulty parameters and performance were used to represent different patients. The number of difficulty parameters as well as the amount of noise was varied. In both simulations the target performance was set to 60%.

C. Study with healthy subjects

In order to test the applicability of the algorithms to reality we conducted a study with 12 healthy subjects playing the spheroids game. The subjects were between 24 and 33 years old, 8 males and 4 female, all except one right handed. The subjects were divided into two groups; the *random-search group* was playing the game with the random-line-search algorithm and the *predictive-group* was playing the game with the predictive-search algorithm. The difficulty parameters were updated every 20 spheres. The session lasted for 50 updates (15-20 min). All subjects were naïve to how the difficulty parameters were controlled. They were instructed to try to hit as many spheres as possible, remain focused throughout the session and pay equal attention to the spheres arriving on both their left- and right-side. In order to control the adaptability of the algorithms to a lateralization of the left and right performance, as seen in stroke patients, we applied a time delay between the movements of the real and the virtual arm for one arm (dominant / non-dominant counterbalanced between groups). We refer to the affected side as the *impaired* arm and the opposite arm the *normal*, even though we are well aware that it is not a realistic emulation of hemiparesis. The target performance was either 60%, 70% or 80%, between groups.

The two algorithms were configured to produce a good trade-off between the spread of the difficulty parameter and performance error given the results obtained from the simulations.

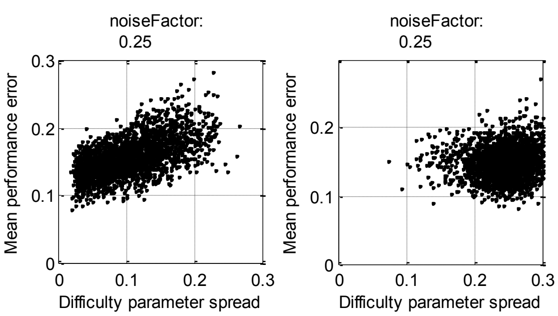

Fig. 2. Results of simulation 1: Mean performance error plotted against difficulty parameter spread. (Random-line-search left, predictive-search right.)

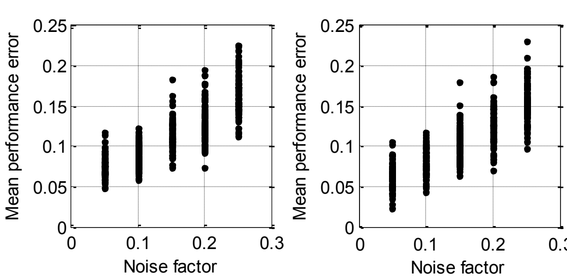

Fig. 3. Results of simulation 1: Mean performance error plotted against level of noise. (Random-line-search left, predictive-search right.)

III. Results

A. Simulations

We measure the mean performance error by calculating the mean of the absolute values of the difference between estimated performance and target performance. To ensure that we only regard the data after both algorithms have converged to the target performance we only include the results from the last 25 (out of 50) updates of each session. The spread of the difficulty parameter was calculated as the mean of the standard deviation of each of the difficulty parameters over the last 25 updates.

The results show that both algorithms do adapt the challenge level by changing the difficulty parameters minimizing the performance error. (Fig. 2). For the random-line-search we can observe a trade-off between parameter spread and performance error, i.e. the higher the spread the higher the error (Fig. 2). In contrast, predictive-search overcomes this limitation and higher spread values can be obtained without increasing the performance error. Figure 3 shows how the mean performance error of both algorithms varies with increasing levels of noise while figure 4 shows how the error varies with increasing number of difficulty parameters. As expected we can observe an increase in the error for both cases. It is however worth noticing that the error is not increasing exponentially. This shows that the algorithms are robust both to noise as well as to a higher number of parameters.

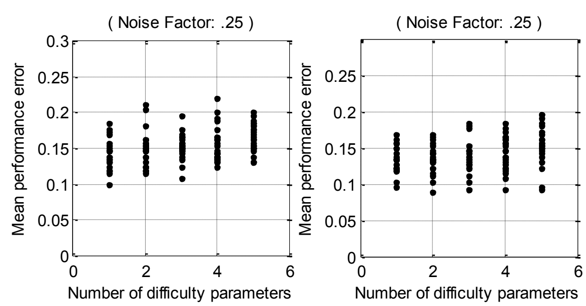

Fig. 4. Results of simulation 2: mean performance error plotted against number of difficulty parameters. (Random-line-search left, predictive-search right.)

B. Study with healthy subjects

For the study with healthy subjects we calculated the mean performance error and difficulty parameter spread in the same way as in the simulations. Figure 5 shows the relation between the spread and the error. We can observe a similar pattern as in the simulation. Neither the spread nor the mean performance error is significantly different for the impaired and normal arms, P-values: 0.67 (mean performance error, random-search group), 0.76 (mean performance error, predictive group), 0.43 (difficulty parameter spread, random-search group), 0.58 (difficulty parameter spread, predictive group). Comparing the spread of the difficulty parameters for the two algorithm shows that the spread is significantly higher for the predictive-search group (p-value < 0.0001). The mean performance error is not significantly different between the groups (p-values: 0.6460). Thus the predictive search algorithm allows for a higher spread with a similar performance error as the random-line-search algorithm.

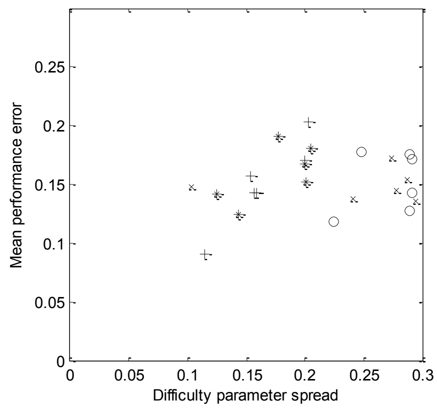

Fig. 5. Mean performance error and difficulty parameter spread for all subjects. (+ : Impaired arm, random-search group. * : Normal arm, random-search group. x : Impaired arm, predictive search group. o : Normal arm, predictive-search group.)

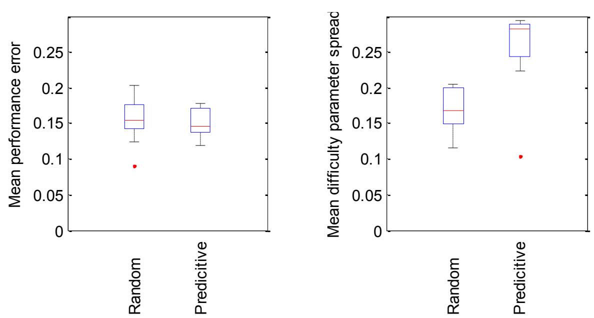

Fig. 6. Distribution of the mean performance error(left) and the mean difficulty parameter spread (right) of the both the impaired and normal arm for both groups. Random-search mean performance error: 0.1506 (σ = 0.0197), Predictive-search mean performance error: 0.1554 (σ = 0.0311), Random-search mean difficulty parameter spread: 0.1698 (σ = 0.0328), Predictive-search mean difficulty parameter spread: 0.2588 (σ = 0.0504).

Figure 6 shows the distribution of the dependent variables for the two groups. To compare these values to the current RGS implementation we extracted the spread of the difficulty parameters and the performance error from the recent study with acute patients [2]; mean performance error: 0.2205 (σ = 0.0148), mean difficulty parameter spread: 0.2016 (σ = 0.0177). We can see that the values are in a similar range as for the two proposed algorithms.

IV. Discussion

To investigate the possibilities to automatize the adaptation of a rehabilitation task to the performance of the RGS users, we developed and tested two different algorithms. We showed that both algorithms allowed adapting the challenge level where the predictive-search algorithm allowed a wider spread in the difficulty parameters while maintaining the performance error at a low level. Learning an adequate user model does however imply that there are sufficient repetitions of the task. In cases where the performance can only be evaluated sparsely the random-line-search algorithm may generate better results, as it does not require any learning. However in the study with the healthy subjects, both algorithms converged on the target performance within ten updates (with one exception in the predictive group) and there were no significant differences between the groups. The results from our study cannot be directly compared to the corresponding values from the version of RGS currently used for rehabilitation, since the games are not identical. Nevertheless, the sizes of the error and the spread for both groups are of the same magnitude as the values extracted from the data from the previous study with acute patients. Thus, without the need of pre-evaluation of the game the adaptation algorithms presented in this paper are able to individualize the challenge posed by a rehabilitation task to each user. As the algorithms make little assumptions on the structure of the game and can operate on an arbitrary set of parameters they can easily be applied to a multitude of therapy scenarios.

References

[1] C. D. Mathers and D. Loncar, "Projections of global mortality and burden of disease from 2002 to 2030.," *PLoS Med.,* vol. 3, p. e442, 2006.

[2] S. M. Lai, *et al.*, "Persisting consequences of stroke measured by the Stroke Impact Scale," *Stroke,* vol. 33, pp. 1840-4, Jul 2002.

[3] A. Huber, "Rehabilitation of homonymous hemianopsia," *Klinische Monatsblätter für Augenheilkunde,* vol. 216, p. 90, 2000.

[4] H. Kelly, *et al.*, "Speech and language therapy for aphasia following stroke," *Cochrane Database Syst Rev,* p. CD000425, 2010.

[5] C. Watkins, *et al.*, "Prevalence of spasticity post stroke," *Clinical rehabilitation,* vol. 16, p. 515, 2002.

[6] R. Robinson and G. Spalletta, "Poststroke depression: a review," *Canadian journal of psychiatry. Revue canadienne de psychiatrie,* vol. 55, p. 341, 2010.

[7] M. L. Dombovy, "Understanding stroke recovery and rehabilitation: current and emerging approaches," *Curr Neurol Neurosci Rep,* vol. 4, pp. 31-5, Jan 2004.

[8] S. Sonoda, *et al.*, "Full-time integrated treatment program, a new system for stroke rehabilitation in Japan: comparison with conventional rehabilitation," *Am J Phys Med Rehabil,* vol. 83, pp. 88-93, Feb 2004.

[9] G. Kwakkel, *et al.*, "Effects of augmented exercise therapy time after stroke: a meta-analysis," *Stroke,* vol. 35, pp. 2529-39, Nov 2004.

[10] J. W. Krakauer, "Motor learning: its relevance to stroke recovery and neurorehabilitation," *Curr Opin Neurol,* vol. 19, pp. 84-90, Feb 2006.

[11] E. M. Steultjens, *et al.*, "Occupational therapy for stroke patients: a systematic review," *Stroke,* vol. 34, pp. 676-87, Mar 2003.

[12] D. A. Braun, *et al.*, "Motor task variation induces structural learning," *Current Biology,* vol. 19, pp. 352-357, 2009.

[13] S. S. Kantak, *et al.*, "Neural substrates of motor memory consolidation depend on practice structure," *Nature Neuroscience,* vol. 13, pp. 923-925, 2010.

[14] M. S. Cameirao, *et al.*, "Neurorehabilitation using the virtual reality based Rehabilitation Gaming System: methodology, design, psychometrics, usability and validation," *J Neuroeng Rehabil,* vol. 7, p. 48, 2010.

[15] M. S. Cameirao, *et al.*, "Virtual reality based rehabilitation speeds up functional recovery of the upper extremities after stroke: a randomized controlled pilot study in the acute phase of stroke using the Rehabilitation Gaming System.," *Restorative Neurology and Neuroscience,* In Press.

[16] G. Rizzolatti, and Craighero, L., "The mirror-neuron system.," *Annu Rev Neurosci,* vol. 27, pp. 169-192, 2004.

[17] R. M. Yerkes and J. D. Dodson, "The relation of strength of stimulus to rapidity of habit formation," *Journal of comparative neurology and psychology,* vol. 18, pp. 459-482, 1908.

[18] M. Csikszentmihalyi, *Flow: The classic work on how to achieve happiness*: Rider London 2002.

[19] S. J. Russell, et al., Artificial intelligence: a modern approach vol. 74: Prentice hall Englewood Cliffs, 1995.

[20] S. S. Haykin, *Neural networks: a comprehensive foundation*: Prentice hall Englewood Cliffs, 1999.