Performance based upper extremity training: a pilot study evaluation with the GENTLE/A rehabilitation system

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***Abstract*—Robots as rehabilitative devices are increasingly utilised in research in this area given their capability to offer repetitive task-oriented training and potentials to augment therapies with more interactive mediums. Various parameters recorded by these rehabilitation robotic devices could inform the therapists about the recovery and thereby allow them to tailor the training according to the performance of the patient. The GENTLE/A rehabilitation system uses the parameters recorded by the HapticMaster robot to identify the leading/lagging performance of the user interacting with the system. Using these performance indicators we proposed a performance based training algorithm that was evaluated during this pilot study with healthy participants. The algorithm could successfully adapt the task difficulty level by altering the resistance offered to the movement of the user. This performance based training algorithm could be enhanced in future to offer isokinetic training. Isokinetic training can identify weak muscle groups and help the therapists recommend a rehabilitation programme for targeted muscle-groups.**

Keywords- Stroke rehabilitation, upper-extremity, adaptive, performance-based training

I. Introduction

Research on global burden of disease [1] shows that Cerebrovascular accident (stroke) is one of the leading contributors for burden of disease in high and middle-income countries. Statistics project that stroke would continue to remain the second major cause of death in the world by 2030 [2]. Given these statistics and with increasing demand for rehabilitation, the need for advanced devices that can assist the therapists to offer rehabilitation has greatly increased. The primary demand from such rehabilitative devices is to reduce the therapist monitoring time and make the rehabilitative training partly self-manageable. This is also thought to encourage the patients to feel in control of their training and motivate them to train for longer durations. In post-stroke recovery early interventions during sub-acute and acute phases for durations suitable to patient's condition and repetitive training are believed to be more effective [3], [4]. Robotic rehabilitation devices are capable of offering these features and in addition could also record several patient parameters that can inform the therapist about the progress in the recovery. The GENTLE/A system is one such device that can offer rehabilitation to upper-limb impaired stroke patients.

If the rehabilitative training has to be made self-manageable (at least partly), the robotic device should autonomously adapt to the performance of the user. The main goal of our research with the GENTLE/A system is therefore to enhance the adaptability of the rehabilitation system. In order to achieve this the strategy we followed is to (i) identify the parameters that inform about the role of the user/robot during an interaction and (ii) use these parameters as performance indicators to adapt the system. The HapticMaster (HM) [5], the robotic component of the GENTLE/A system, is programmed to follow a reference trajectory (Minimum Jerk Trajectory, (MJT) [6]). HM's end-effector can record position, force and velocity. In our earlier studies [7], [8] with the GENTLE/A system we identified that the difference between the Cartesian coordinates recorded by the HM and the MJT position at a given point in time indicated the leading/lagging status of the user with respect to the robot. This parameter that estimated the contribution of a user during a human-robot interaction (HRI) session was termed as Δ*Effort*.

The whole process of rehabilitation is to retrain and relearn lost motor skills. A rehabilitative training is thought to be useful if it can motivate the patients to train more at the initial stages of recovery and make the task progressively challenging as the recovery happens. So applying this to our research, once the Δ*Effort* parameter identifies that the user is leading the interaction, the task could be made more and more challenging. Using Δ*Effort* and parameters derived from Δ*Effort* (presented in later sections of this article), we proposed a performance based training algorithm. This algorithm would adapt the task difficulty based on the performance of the user interacting with the GENTLE/A system. This algorithm has been evaluated during the current pilot study and the results are presented in this paper.

II. Methods

A. Experimental setup

The HapticMaster (HM) has 3 degrees of freedom with reasonably larger workspace, suitable to offer training for upper-extremity impairments. A Virtual Reality (VR) environment displayed the target points to be reached by the user as coloured balls (Fig.1). An embedded set-up (Fig. 2) was created to test the performance of the users in the presence/absence of real objects alongside virtual objects displayed on the screen.

The participants were asked to hold the ball gimbal (black ball in Fig. 2) attached to the HM's end effector and move from point-to-point in a sequence. The VR environment and audio cues helped the participant to figure out source and target points. The movement beginning at point-k to reach point-(k+1) was referred as segment-k and a set of eight points was chosen for this study.

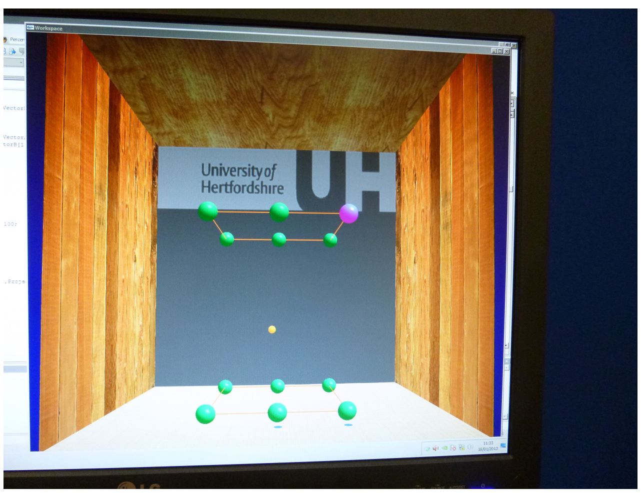

Fig. 1. VR environment showing virtual targets

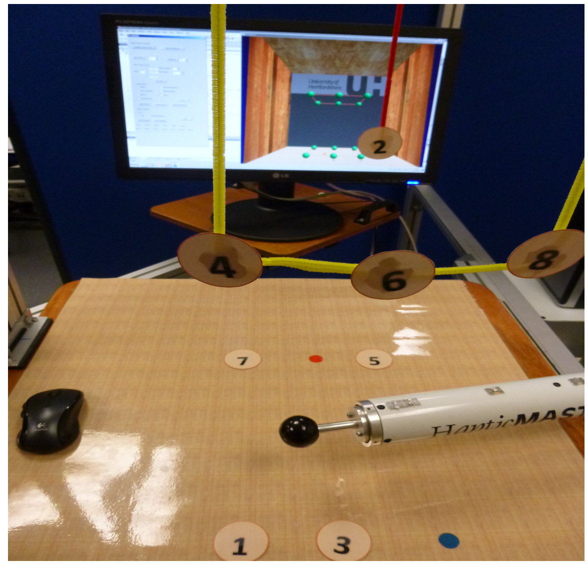

Fig. 2. Embedded environment showing both real and virtual targets

B. Terminology and Parameters

Our previous studies with the GENTLE/A rehabilitation system informed us that during a HRI session, the Cartesian coordinates recorded from the HM's end-effector could indicate the leading/lagging status of the user. The HM could be programmed to operate in different modes with varying roles of the user versus the HM. The two modes in which the HM was operated during this pilot study were

1. *Passive*: User remained *passive* while the HM executed point-to-point movements according to a reference trajectory (MJT).

2. *Active*: User *actively* executed the point-to-point movements while the main role of the HM was to record the data and offer corrective haptic assistance when the user deviated beyond a set limit from the reference path.

During the execution of any segment (point-to-point movement), data was sampled at 50 msec time intervals. The Cartesian coordinates were recorded at every sampling interval and various parameters were calculated to indicate the performance of the user (see Fig. 3 for a pictorial representation).

Guiding vector: Straight line vector joining source and target points of a segment.

Actual vector: Vector joining source to the current position achieved by the user at the given point in time.

MJT vector: Vector joining source to the MJT position at the given point in time.

$Effort_{Actual}$: Vector projection of 'Actual vector' onto the 'Guiding vector'.

$Effort_{MJT}$: Vector projection of 'MJT vector' onto the 'Guiding vector'.

ΔEffort: Performance indicator that could successfully indicate the leading/lagging performance of the users in earlier studies with the GENTLE/A system.

$$\Delta Effort = Effort_{Actual} - Effort_{MJT}$$

%Contribution: Indicates leading/lagging performance of the user with respect to the reference trajectory (MJT) as a percentage.

$$\%Contribution = \frac{\Delta Effort}{Effort_{MJT}} * 100$$

%Difficulty(LOW): The difficulty levels during a segment were altered between high and low based on the algorithm presented in the next sub-section. *%Difficulty(LOW)* was calculated as a percentage of the number of samples for which the difficulty level remained low to the total number of samples collected during that segment.

$$\%Difficulty(LOW) = \frac{Sample\ Count_{LOW}}{Total\ Sample\ Count_{Segment}} * 100$$

%Difficulty(HIGH) was similarly calculated from number of samples for which the task difficulty level remained high during a segment.

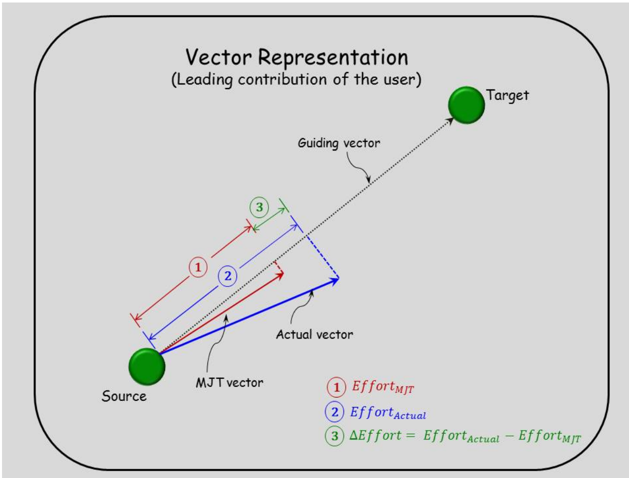

Fig. 3. Vector representation

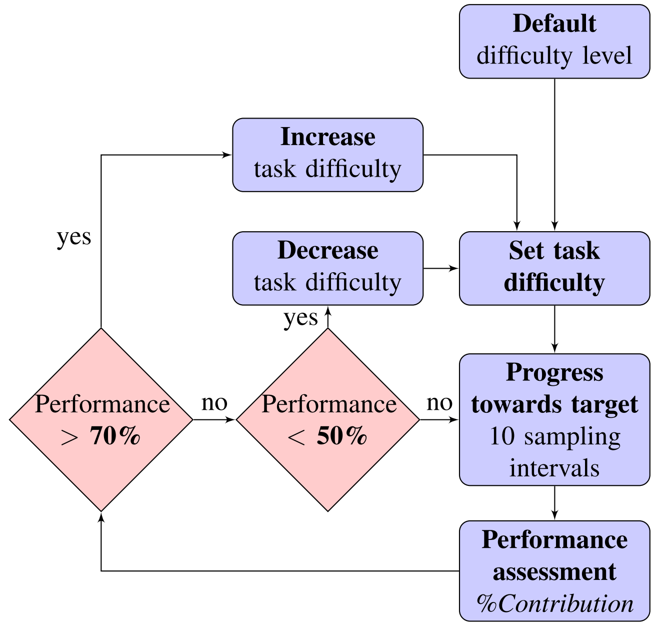

Fig. 4. Flow-chart representation of Performance based training algorithm

C. Algorithm

Our research with the GENTLE/A rehabilitation system aims to enhance the adaptability of the system according to the performance of the user. Δ*Effort* could successfully indicate the leading-lagging status of the user in our earlier studies with the GENTLE/A system. Utilising the *%Contribution*, derived from Δ*Effort*, as a performance indicator we proposed an adaptive algorithm that would autonomously alter the task difficulty. The algorithm is implemented during the 'active' mode of operation. The choice of the mode was to enable testing the adaptability algorithm when the user was actively contributing to the movement. The active mode uses a *ratchet* function *(E(t))* [9], that allows the movement to progress towards the target only when the user actively contributes and leads the activity.

$$E(t) = (p(t)-p'(t))^2$$

where *p'(t)* is the actual position of the robot and *p(t)* is the position the robot has to be according to the reference trajectory (MJT) at the time t. Thus for each two adjacent time samples such as t_1 and t_2 where $t_2 > t_1$ we can calculate $E(t_1)$ and $E(t_2)$. If $E(t_2) < E(t_1)$ then t_1 is adjusted to be the new value t_2. Hence in the active mode Δ*Effort*, always shows a leading contribution from the user. The parameter *%Contribution* therefore gives the amount (in percentage) by which the user is leading the MJT. We designed our algorithm based on the *'personalised training module'* implemented on a rehabilitation gaming system and tested with upper-limb impaired stroke sufferers [10]. The algorithm is presented as a flow-chart (Fig. 4). As a virtual spring-damper combination was used to guide the movement in line with the reference trajectory, to change the task difficulty we altered the stiffness of the virtual spring created at the HM's end-effector. At the beginning of every segment, the task difficulty was set to a default value (default spring stiffness =300 N/m). After every 10 samples (=0.5s), the *%Contribution* was calculated and the task difficulty was changed according to teh algorithm. The difficulty level was raised by increasing the spring stiffness by 50% (high spring stiffness = 450 N/m) which in turn increased the resistance offered by the HM to the user's movement. Similarly, the difficulty level was lowered by decreasing the spring stiffness by 25% (low spring stiffness =225 N/m). Therefore the spring stiffness varied between the default, higher and lower values during the execution of a segment based on the performance of the user. These assignments were set after a series of trial and error experiments assessing how the system felt with stronger and weaker springs but further work in this area will consider auto-adjustment of stiffness proportionate to *%Contribution*.

D. Protocol

The pilot study included eleven healthy participants (2 female and 9 male), age ranging 26.9 $\pm$ 6.6 (mean $\pm$ standard deviation). Written informed consent was obtained from each participant before inclusion in the study and ethical approval of the evaluation protocol was obtained from the University's ethics committee (under University of Hertfordshire approval number 1213/28).

During an experimental session, participants were briefed about both the modes and asked to practice these modes to understand how the movement progressed in a sequence from Point-1 to Point-8 with a small delay of 1s between consecutive segments. This initial training helped the participants to understand their role during each mode. In the passive mode the participants were advised to remain passive, gently holding the ball gimbal allowing the HM to execute the activity. While in the active mode, participants were instructed to take charge of the activity. The screen displaying the VR was made invisible to the participant by covering it with an opaque board during the active mode. The intention of this act was to encourage the participants to notice the real objects representing the targets and pay attention to the audio cues.

Once the participant was comfortable with the system, the active mode was executed five times. Both virtual and real targets were visible during these five iterations and the choice of using either as a reference for practice was left to the participant. During these iterations the system autonomously tuned the difficulty of the task according to the algorithm presented in (Fig. 4). Towards the end of the fifth iteration the participant was given a small questionnaire to complete.

III. Results and Analysis

The main aim of this pilot study was to evaluate the performance of the adaptive algorithm. We carried out this evaluation using two sources of data obtained during the study, one being the data recorded by the system and the other being the feedback obtained through questionnaires. As a first step the data recorded by the system during the five repetitions of the active mode was analysed to study if the algorithm implemented, autonomously tuned the resistance based on the performance of the participant. The performance of the participant was assessed every 10 sampling intervals (=0.5s) and the task difficulty was altered accordingly by the algorithm.

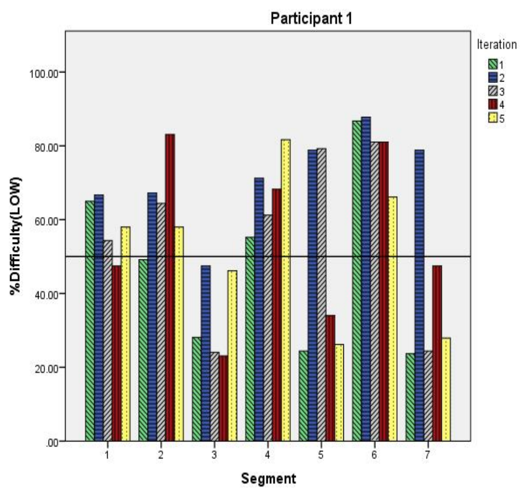

Fig. 5. Performance of Participant 1

Every segment was executed five times by each participant during the five repetitions of active mode. The number of sampling intervals for which the task difficulty remained low (low spring stiffness) was counted and from this *%Difficulty(LOW)* was calculated for each segment during an iteration. Similarly, *%Difficulty(HIGH)* was calculated from the number of sampling intervals at high task difficulty level (high spring stiffness) for that segment. Fig. 5 - Fig. 7 illustrate the performance in terms of *%Difficulty(LOW)* during all the five iterations of the active mode for three of the participants from the study. The plots show that the task difficulties, not only varied from participant to participant but also between different segments executed by the same participant as well as within iterations of the same segment.

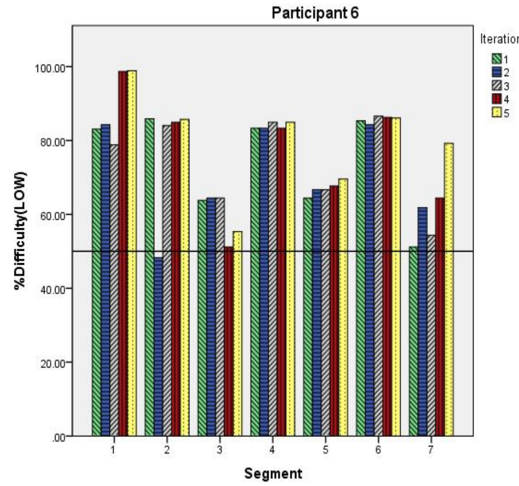

Fig. 6. Performance of Participant 6

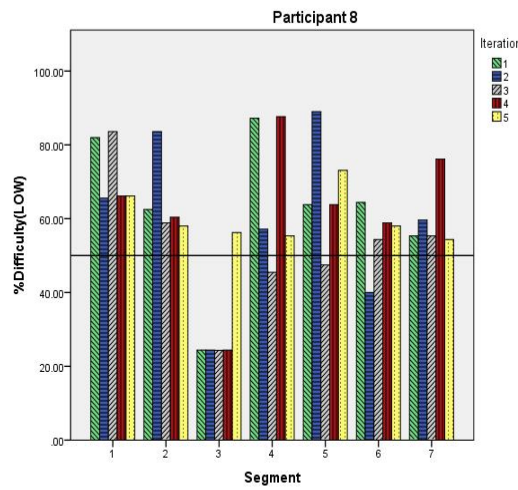

Fig. 7. Performance of Participant 8

We used simple rules presented in Table I to study these plots. Applying these rules to segment-5 of Fig. 5, it can be inferred that during second and third iterations the participant executed major part of the segment at low task difficulty level. Likewise varying patterns in the performances of Participant 6 and Participant 8 could be observed from Fig. 6 and Fig. 7 respectively. The performance of the system as projected by the data recorded by the HM is highlighted through these plots.

The next step of data analysis was to evaluate the performance of the system as perceived by the participants. The summary of the feedback received through questionnaires is presented in Table II. When the participants were asked to rate the challenge in the task, 5/11 participants rated the challenge

TABLE I
PERFORMANCE EVALUATION RULES

%Difficulty(LOW)	**Performance evaluation**
> 50	major part of the segment executed at LOW task difficulty level
$<= 50$	major part of the segment executed at HIGH task difficulty level

TABLE II
QUESTIONNAIRE SUMMARY

Participant	**Challenge**[a]	**Difference**[b]	**Usefulness of embedded object**[c]
1	2	Yes	3
2	4	No	5
3	3	Yes	4
4	3	No	4
5	5	Yes	5
6	2	No	4
7	3	Yes	5
8	4	Yes	5
9	4	No	4
10	1	No	4
11	4	Yes	5

[a]on a 5-point Likert Scale 1-Not at all challenging and 5-Very challenging
[b]difference in the task difficulty level perceived by the participant as the movement progressed from *source* to *target* of a segment
[c]on a 5-point Likert Scale 1-Not at all useful and 5-Very useful

as 'somewhat challenging' or 'very challenging', 3/11 rated the challenge as 'neutral and 3/11 rated as 'not very challenging' or 'not at all challenging'. For the difference perceived as the movement began at a source point and progresses towards a target point of a segment, 6/11 participants responded with an 'Yes'. The comments received when the participants were asked to explain the difference were like 'more difficult', 'had to put more effort', 'I felt the resistive forces increased, so had to put extra effort' and so on. These comments from the participants suggested that the system indeed tuned the task difficulty according to the performance of the participant. We attempted to examine if there existed any patterns between the performance of the system as perceived by the user and the performance of the system as projected by the system recorded data.

Assumption: Our underlying assumption while carrying on this examination was, if the performance of a participant is spread out between high and low task difficulty levels during the entire experimental session, this would prompt the participant to perceive the difference in system's response to his/her inputs. Likewise if the performance is confined mostly to one of the task difficulty levels, there is a greater chance that the variation between the task difficulty levels would go unnoticed by the participant.

In order to estimate the performance of the participant during the active mode we calculated the sum of *%Difficulty(LOW)* across the five iterations of each segment and extended the rules presented in Table I to '$>$ 250' and '$<=$ 250' for low and high task difficulty levels respectively. Fig. 8 presents a segment-wise summary of the performance of all the participants in the study. The plot also groups the participants according to their response (Yes/No) for the question 'difference perceived in the task difficulty level'. The left half of the plot shows the system performance for participants with the questionnaire response 'Yes' and the right half shows the system performance for the participants with the questionnaire response 'No'. For participants 1, 3 and 11 the performance was spread out between high and low task difficulty levels (see Fig. 8 above and below *%Difficulty(LOW)* =250) and the perceived a difference in the system's response. (questionnaire response 'Yes') and this was in agreement with our assumption. Similarly, for participants 2, 4, 6, 9 and 11 the performance was confined to low task difficulty level (see Fig. 8 above *%Difficulty(LOW)* =250) and the participants could not perceive a difference in the system's response (questionnaire response 'No') and this was also according to our assumption. But the performance and questionnaire responses of participants 5, 7 and 8 were not according to our assumption. In summary, for 8/11 participants the system's response and the participant's observation matched.

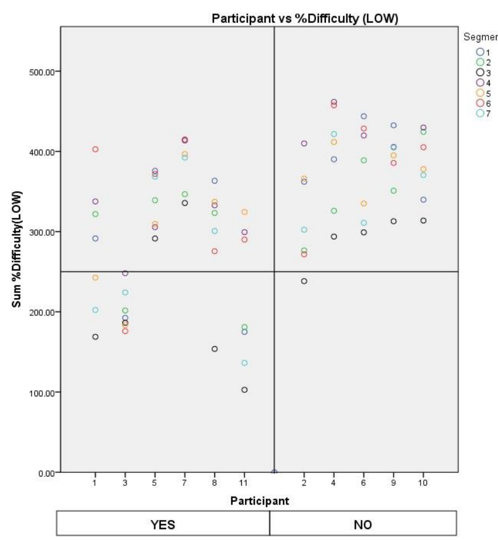

Fig. 8. Performance summary plot of all the participants

An earlier study [11] conducted by our research team showed that the performance of healthy participants significantly differed between completely virtual and embedded environments. Since patients with stroke often suffer from cognitive impairments, this might effect their performance in a VR environment. This we believe could be avoided if a real object is presented as a target and might also bridge the gap between the training and the real life scenarios. We therefore included an embedded set-up alongside the VR in this pilot study (see Fig. 2) to investigate further. The feedback received for 'usefulness of the embedded object' through the questionnaire supports our previous findings. 5/11 participants responded with 'Very useful' for the embedded environment, 4/11 with 'somewhat useful' and 1/11 was 'neutral'.

IV. Discussion and Conclusion

The main goal of this pilot study was to evaluate the performance-based adaptive training algorithm implemented on the GENTLE/A rehabilitation system. The system recorded data from the study showed that the training algorithm did indeed tune the task difficulty based on the performance of the participant. Comparing questionnaire with system recorded performance parameters, a greater share of responses received through the questionnaire also confirmed the difference in the task difficulty level as perceived by the participants.

However, while we highlighted our assumption, that a spread out of the performance between low and high task difficulty levels could inform on participants perception of a difference in system's response, this was indeed not the case for participants 5, 7 and 8. A potential explanation for this observed difference could be that high and low task difficulty levels in our data analysis follows an assignment of stiffness values to low and high categories. This is while individual's perception of task difficulty does not necessarily relate to such assignment. Therefore we point out that results obtained regarding perceived level of difficulty using questionnaires might not be suited for alignment with the *%Difficulty(LOW)/(HIGH)* calculations. However, we maintain that *%Difficulty(LOW)/(HIGH)* can provide a good insight into dynamic change of difficulty during different interactive sessions. Using *%Difficulty(LOW)/(HIGH)*, it was noted that the adaptive tuning did indeed work for all participants as reflected by changes in difficulty levels for different segments. We intend to also use recorded forces during additional analytical work to identify if changes in difficulty levels are in line with changes in forces recorded, thus highlighting if disparity in perception in relation to *%Difficulty(LOW)/(HIGH)*, would also be the case for the recorded forces during interaction. In our upcoming study, we aim to enhance the adaptive algorithm to identify participant-specific optimal values for low and high stiffness and evaluate this enhanced algorithm with a greater number of participants.

The embedded environment was rated as very useful by the majority of the participants. Training in an embedded environment with real objects as targets as opposed to complete virtual environment, we presume, would not only improve the performance of the stroke sufferers but also motivate them to transfer the skills to activities of daily living. This deserves further inspection in clinical settings with stroke sufferers. The performance based adaptive training algorithm implemented on the GENTLE/A rehabilitation system alters the task difficulty by altering the resistance offered by the system. In future we aim to use this variable resistance training to design isokinetic training exercises. Isokinetic training, apart from helping the patient to improve muscular strength and endurance, also helps the therapists to identify weak muscle groups and thereby tailor the rehabilitation programme.

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