# The influence of haptic support algorithm dynamics on the efficacy of motor learning

## Vpliv dinamike algoritmov haptične podpore na učinkovitost motoričnega učenja

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## Abstract

**Background:** Repetitive task training, delivered either by a therapist or haptic robot is the core of modern rehabilitation of movement. In the current rehabilitation, robotics-based movement training the level of haptic support assisting the movement is rather stationary and may remain the same for periods of days. The aim of this paper was to investigate the influence of haptic support algorithms (HSA) dynamics on the outcome of motor learning.

**Methods:** Twenty-seven neurologically intact participants, divided into three groups supported by dynamically different HSA, played a rather demanding two degrees of freedom motor task (virtual reality based table football) to learn wrist movements with their inferior arm. The evaluation before training without robotic support was followed by the training session and concluded with evaluation after training without robotic support.

**Results:** The results showed significant improvement in all three groups, but the statistical analysis reveals the difference within groups. The selection of the HSA that is appropriate for the given motor task had a significant influence on the level of acquired motor skills after the training period.

**Conclusions:** The results of this study suggest that for every motor task or equivalently for every motor ability of a particular subject such a HSA scheme exists and should be implemented that maximizes training effects in a limited number of training attempts.

## Izvleček

**Izhodišča:** Sodobna rehabilitacija temelji na intenzivnih treningih gibanja, ki jih podpira bodisi haptični robot bodisi fizioterapevt, ki sledi predpisanim protokolom. Številne raziskave so pokazale, da vadba enostavnih in ponavljajočih se funkcionalno usmerjenih nalog učinkovito zmanjša motorično prizadetost roke, medtem ko na izboljšanje funkcij roke nima pomembnega vpliva. Vzrok je urjenje v nespremenljivih pogojih in predvidljivo delovanje haptične naprave. Študije plastičnosti možganov nakazujejo, da bi bilo potrebno za uspešno učenje funkcionalnih dejavnosti v vadbo vključiti določeno mero nadzorovane variabilnosti, ki bi spodbujala razvoj ustreznih motoričnih vzorcev. To pa zahteva merjenje trenutnih zmožnosti uporabnika in prilagajanje ravni haptične podpore rehabilitacijskih robotov. S študijo smo želeli raziskati vpliv dinamično različnih algoritmov haptične podpore (*angl.* haptic support algorithms, HSA) na učinkovitost motoričnega učenja, pri katerem raven haptične podpore postopno zmanjšujemo glede na napredek v motoričnih sposobnostih.

**Metode:** Sedemindvajset zdravih oseb smo razdelili v tri skupine z različnimi shemami HSA. Za učenje gibov roke smo uporabljali simulacijo ročnega nogometa, pri katerem oseba z nedominantno roko in s pomočjo haptične naprave upravlja virtualnega nogometaša. Protokol je zajemal vrednotenje pred treningom in brez haptične pomoči, trening gibanja s pomočjo haptične naprave in z izbrano shemo HSA ter vrednotenje po treningu.

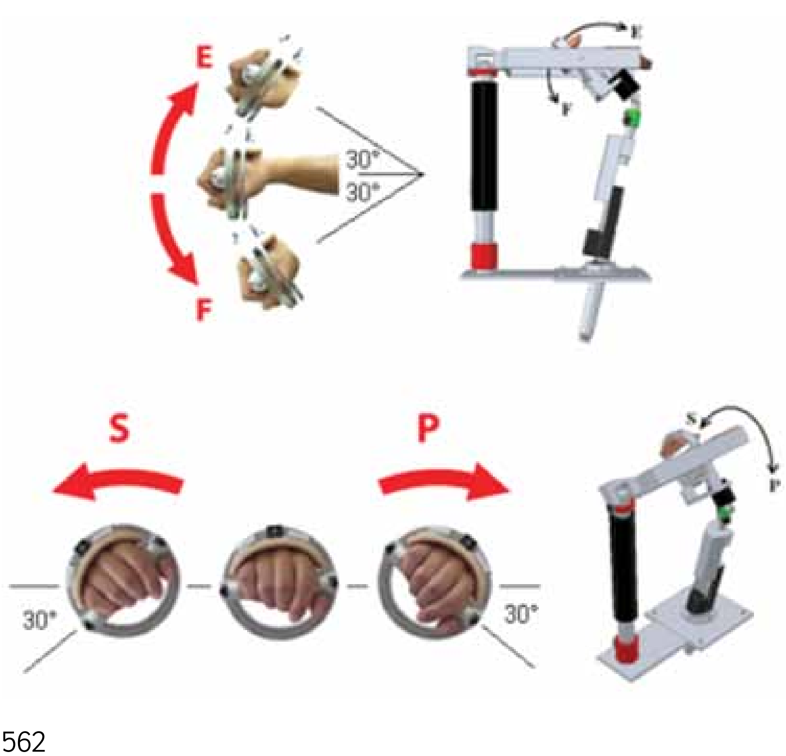
**Rezultati:** Rezultati kažejo na bistveno motorično izboljšanje v vseh treh skupinah, vendar pa statistična analiza kaže, da med skupinami obstajajo razlike. Izbira sheme HSA, ki je primerna za dano nalogo, pomembno vpliva na izboljšanje motoričnih sposobnosti po obdobju treninga.

**Zaključki:** Študija je pokazala, da je za vsako motorično nalogo oz. za vsako motorično sposobnost posameznika potrebno uporabiti takšno shemo HSA, ki v omejenem številu poskusov maksimizira učinek treninga.

## Introduction

In the European Union an estimated 1.1 million new stroke events occur every year and currently 6 million subjects that have survived stroke live in these countries. In the future, the number of new stroke events will increase to 1.5 million per year in 2025 due to demographic changes. Mostly in the elderly population the neurological injury is a leading cause of permanent disability. The primary cause of neurological injury is stroke, where first time strokes result in an acute sensorimotor hemiparesis of the contralateral upper and/or lower limbs.[1] The vast majority of stroke survivors suffer a loss of control of the arm and hand or have reduced manual dexterity. They are unable to perform everyday tasks and when they try to perform arm or wrist movements, the trajectories are abnormal. The traditional way of motor re-learning is physical therapy, which enhances functional recovery after stroke, but it is labor-intensive and increasingly expensive due to a growing number of patients or rather scarce resource of physiotherapists.[2] The therapy centers are forced to treat patients within a short period of treatment time. Therefore, it is imperative to find solutions for effective therapy. The rehabilitation robotic devices for upper extremity training,[3-8] which are attached to the limbs of patients and assist them to complete movements, are used to accelerate the recovery after stroke. Some of them are using stiff controllers, which move the extremity along the desired trajectory without active participation from the patient. This kind of training does not take into account a key signal that drives human motor learning – a kinematic error, and has a limited therapeutic effect. In order to allow some kinematic error, most of the devices use impedance control, meaning that the robots apply forces, which are proportional to the error between desired and current position. Thus, robots keep the extremity near the desired trajectory with a predefined fixed level of assistive force and allow some interaction with the patient. The amount of assistive force could vary between patients with different impairment levels, and also within each individual due to recovery progress. In the current rehabilitation robotics based movement training the level of haptic support assisting the movement is rather stationary and may remain the same for periods of days. Furthermore, constant level of applied force would progressively depress voluntary control instead of promoting it.

**Figure 1:** The UHD-robot allows 2-DOF movements in the tak: wrist flexion/extesion and pronation/supination.




Studies in human motor learning[9-16] have shown that humans learn novel motor tasks in a way where after each repetition the motor commands are modified according to the results of a previous attempt. In such a learning scheme it is crucial that the modifications made to the previous motor command set are such that converge in an improved performance. Inspired by the motor learning of novel tasks in neurologically intact humans, similar variable or assist-as-needed haptic support schemes were developed also for rehabilitation robotics supported reaching-movement training in post-stroke individuals.[9-11] The common feature of these control schemes is the variation of haptic support delivered by a rehabilitation robot after each attempt, where the level of robotic support is increased proportionally by the kinematic error between the desired and reached target and decreased proportionally by a suitable "forgetting-factor" which prevents a human from surren-

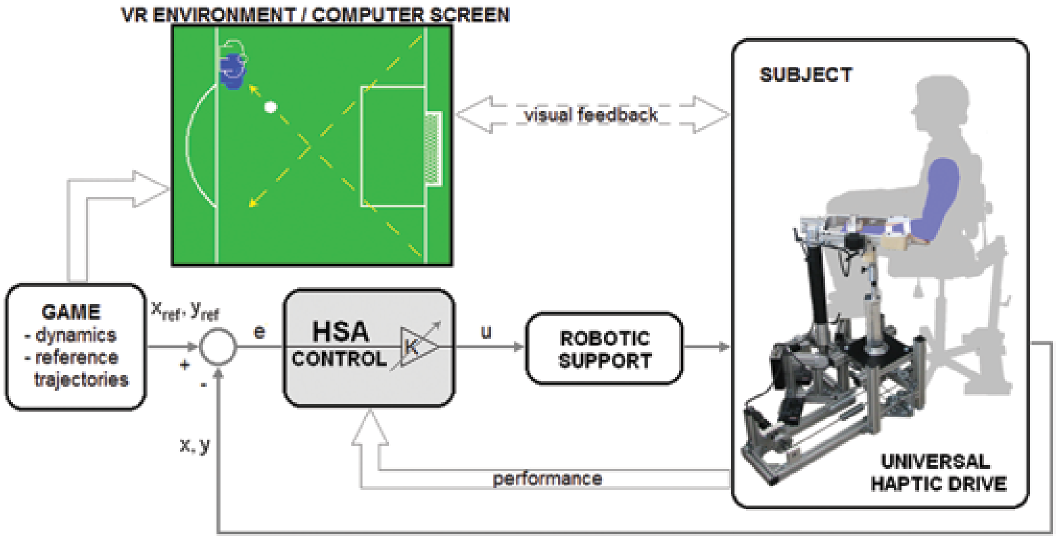



**Figure 2:** Block diagram of the experiment. The subjects perform the task with UHD's handle bar. UHD is supervised by the HSA control, which changes the robot's stiffness level K.

dering the task completion completely on the robot. Some studies also include the internal models of the impairment on which they formulate the assist-as-needed principle as an optimization process, meaning that the robotic movement trainer must minimize a cost function that is the weighted sum of robot force and patient movement error.[11-16] However, the dynamics of motor recovery in a post-stroke population due to brain plasticity is much slower as compared to the neurologically intact individuals' capabilities to learn a new motor task. Therefore, the rehabilitation robotics control schemes that implement changes in robotic support after each movement attempt may be simply too fast regardless of the size of kinematic error and forgetting-factor gains used.

The aim of this paper was to investigate the influence of haptic support algorithm (HSA) dynamics on the outcome of learning of a rather demanding two-degrees-of-freedom motor task in three different groups of neurologically intact individuals that have not differed in their motor performance of this particular motor task before training. All three groups were subjected to the same number of training attempts and have differed in the dynamics of HSA implemented in the rehabilitation robot that provided haptic support during motor task execution. Our hypothesis was that the results of learned motor performance, as measured by kinematic error achieved at the end of training period, will significantly differ between the three dynamically different HSA schemes.

# Methods

## Experimental setup

The experimental evaluation was carried out by means of Universal Haptic Drive (UHD) rehabilitation robot . The UHD has 2 actuated DOFs and is impedance controlled, which implies that the actuators are used as force (torque) sources. This innovative rehabilitation robot enables training of reaching movement as well as wrist movement by a single device.[9] The UHD communicates with MATLAB and Simulink environment via xPC target (Mathworks Inc), where the dynamic of virtual scene, reference trajectories, and haptic robot control were calculated and supervised. The most important feature of our experiment, implemented in a control architecture, was the haptic support algorithm (HSA). The maximum angle of the UHD-robot for wrist training is 30° for flexion and extension movements from the horizontal position of the hand and 30° for pronation and supination movements from the horizontal handle position as shown in Figure 1. Subjects sat on a chair with their torso and arm restrained by means of suitable holders, and grasped the UHD's handle with their inferior arm. The position of the seat was also adjusted in such a way that the forearm was positioned horizontally (Figure 2). Approximatelly 1 m in front of the

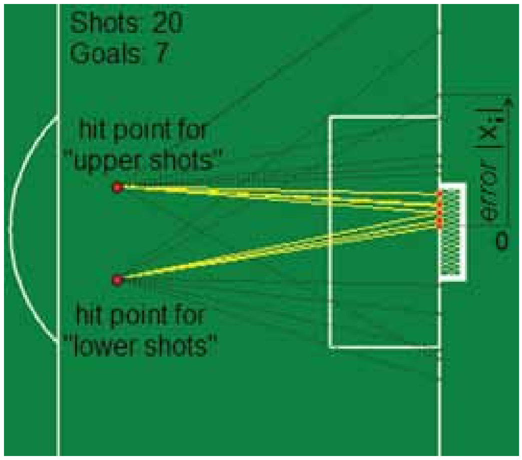



**Figure 3:** Evaluation statistics of goals (yellow lines) and missed shots (dotted black lines). The hit points for upper and lower shots are clearly visible. The performance was calculated on the basis of deviation from the center of goal.

subjects, a 22" LCD computer screen was placed for displaying the virtual reality environment. To create a dynamic environment, the haptic robot was programmed to apply the force field around the desired position, which was proportional to the position error.

## Task

The task for wrist training was a table football game in virtual environment. A vertically moving virtual player was associated with haptic arm, whereas the reference player was indicating the reference trajectories to hit the ball into the goal. The goal width represented the 20 % of whole outline and was always fixed for every subject. Vertical position of the game player was managed by subjects' wrist flexion and extension movements, while rotation around the vertical axis was managed by forearm pronation and supination movement. The aim of the game was to learn specific movements that result in scoring as many goals as possible. In each attempt the ball came randomly from one of two possible predetermined directions as shown in Figure 2, always with the same velocity profile. Thus, we distinguished the upper and lower shots, with separate and independent robot support level. To add a score the subjects had to move the robotic arm with the proper combination of vertical and horizontal velocity components to put the ball into the goal.

## Subjects

Twenty-seven neurological intact adult subjects (19 males, 8 females) participated in the research. The subjects ranged in age from 19 to 35 years (25.4 ± 3.3), three of them were left-handed and the others right-handed. All subjects performed or saw the measurement for the first time. They trained their wrist movements of the inferior arm by the assistance of robotic support. At the beginning of each experimental trial, one of three HSA was randomly chosen for each subject, in a way to form three groups of 9 subjects with different HSA specified as Group 1, Group 2 and Group 5.

## Protocol

The experiment consisted of four parts: preliminary session, evaluation before training, training session and evaluation after training. In the preliminary session the subject got familiar with the UHD-robot and task, and tried approximately 10 shots on goal. Following the preliminary session, the evaluation before training consisted of 20 shots on goal (10 upper and 10 lower shots), with ball direction alternating between upper and lower direction. UHD-robot was operated in zero impedance mode, meaning that the robot did not apply any support forces. Also, the reference player was turned off, so there was no visual information about desired trajectories. The third and the most important part for motor learning was the training session. It consisted of 100 shot attempts on goal, with ball direction (up or down – Figure 2) being randomly chosen in such a way that at the end of the training session exactly 50 upper and 50 lower shot attempts were completed. During training, certain level of robotic support was provided to the subject as determined by one of the three dynamically different HSA (Table 1) and the reference player, who indicated the desired movements, was enabled. The training session was followed by evaluation after training, where the protocol was identical to the evaluation before training. The whole measurement lasted approximately 30 minutes per each subject.

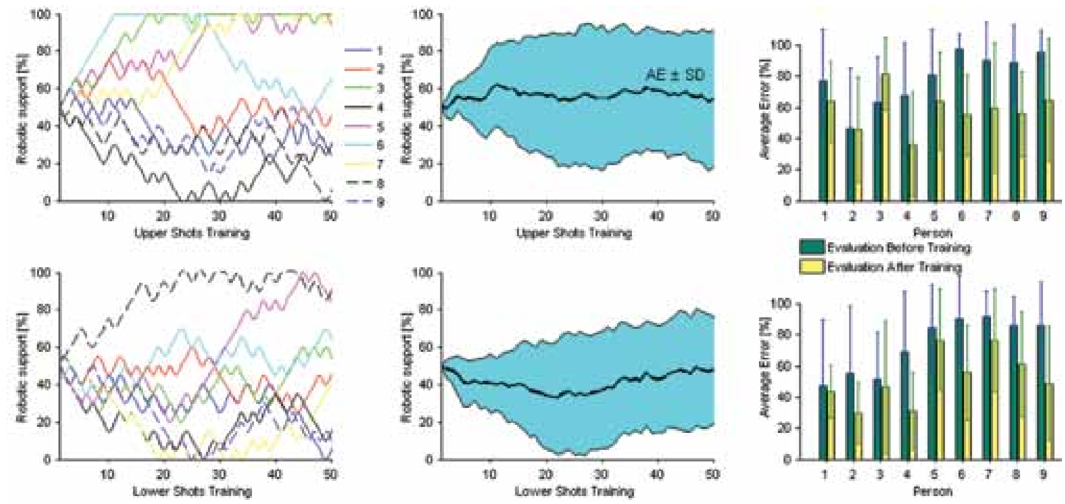



**Figure 4:** The curves of individual robotic assistance during training (left graphs), the average of curves of robotic assistance with corresponding standard deviation (middle graphs) and the evaluation before/after training (right graphs) for Group 1 with HSA that changes the level of haptic support after each shot – Table 1a).

## Haptic support algorithms (HSA)

Three interdependent modules, shown in Figure 2, are important for the control architecture: robotic support, performance and HSA control. Robotic support provides the appropriate force field around the desired trajectory. It is controlled by an input parameter $u$, which is transmitted to the control units of the actuators (motors). Since the robot has two actuators, one for vertical player movements and one for player rotation, the input parameter $u$ has two components, which are proportional to position error. The position error was calculated separately for $x$ (horizontal – player rotation) and $y$ (vertical – player translation) position. Besides visual guidance (reference player), the HSA parameters varied depending on the subject's performance, i.e. depending on the goal score. Here we defined support gain $K$ through which we determined appropriate level of robot's impedance. It varied according to one of the three HSA as described in Table 1 and was related to the robotic support input parameter $u$ as

$$\underline{u} = \begin{bmatrix} u_x \\ u_y \end{bmatrix} = K \begin{bmatrix} e_x \\ e_y \end{bmatrix} = K \begin{bmatrix} x_d - x \\ y_d - y \end{bmatrix} \qquad (1)$$

The first HSA (Group 1) changed the level of haptic support after each shot attempt. Therefore the level of support increased in the case of a missed shot, and decreased in the case of a goal – Table 1a). Second HSA (Group 2) changed the level of haptic support after two consecutive shot attempts. The level of support increased if both shots were missed, remained fixed if one goal was scored, and decreased if both goals were scored – Table 1b). The third HSA (Group 5) changed the level of haptic support after five

**Table 1:** The HSA changes the level of haptic support after a) each shot (Group 1), b) two consecutive shots (Group 2) and c) five consecutive shots (Group 5). According to the subject's performance the support level increases, remains at the same level, or decreases.

| a) 1 shot attempt | | b) 2 shot attempts | | c) 5 shot attempts | |
|---|---|---|---|---|---|
| goals | support | goals | support | goals | support |
| 0 | ↑ | 0 | ↑ | 0 | ↑ |
| 1 | ↓ | 1 | = | 1 | ↑ |
| | | 2 | ↓ | 2 | = |
| | | | | 3 | = |
| | | | | 4 | ↓ |
| | | | | 5 | ↓ |

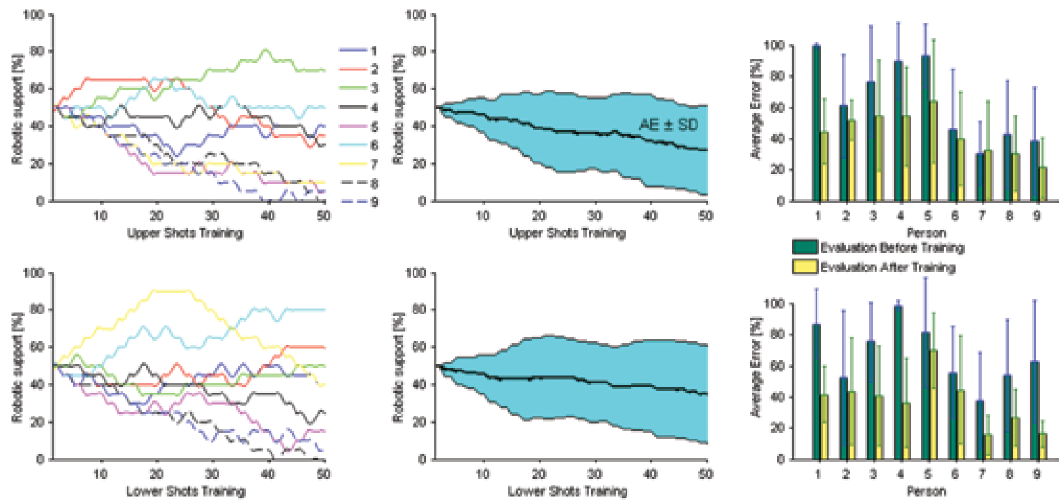



**Figure 5:** The curves of individual robotic assistance during training (left graphs), the average of curves of robotic assistance with corresponding standard deviation (middle graphs) and evaluation before/after training (right graphs) for Group 2 with HSA that changes the level of haptic support after two consecutive shots – Table 1b).

consecutive shot attempts, namely the level of support decreased in the case of four or five goals, remained fixed in the case of two or three goals, and increased if the subject scored one goal at the most – Table 1c). According to these HSA the robotic support step was 5 % and represented the change in robot's stiffness which ranged between zero impedance mode and its maximum value (stiffness 20 Nm/rad). The 5 % step was arbitrarily chosen on the basis of preliminary experiments. The initial value of the robot's stiffness (i.e. training session beginning) was set to 50 % of its maximum value ($K_0 = 0.5\, K_{max}$).

## Performance evaluation

Two performance measures were analyzed to assess subjects' task performance: average error – AE (Equation 2) and standard deviation – SD (Equation 3) for upper and lower shots separately, before and after training. Error was defined as an absolute distance from the goal center $x_i$, when the ball has reached the outline. One example is shown in Figure 3, where hit points for upper and lower shots are clearly visible. The yellow lines represent the goals and dotted black lines represent missed shots. Average error was given in percent of maximum distance from the goal center, which was determined when the ball did not reach the outline (Figure 3 shows two such cases in upper shots). In this case, and in the case if player did not even touch the ball, the 100 % error was recorded. During the training session we also recorded the robotic support (i.e. support gain $K$ in percent of maximum robot's stiffness).

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n}|x_i| \tag{2}$$

$$s = \frac{1}{n-1}\sum_{i=1}^{n}(|x_i| - \bar{x})^2 \tag{3}$$

## Statistical analysis

Individual performances of both evaluation sessions (before and after training) were recorded and reported as the AE ± SD. Upper and lower shot errors were measured and calculated independently. In each group of participants we calculated the average of all individual performances (e.g. average deviations from the center of goal) with corresponding SD. One-way ANOVA analysis was used to compare the crucial aspects of the experiment. A $p$ value less than 0.05 was used to define statistical significance.

## Results

Figure 4, Figure 5 and Figure 6 show the results of all three groups, where left graphs show individual robotic support curves during upper and lower shots training session, middle graphs show the group average of support curves with corresponding standard deviation, while right graphs show

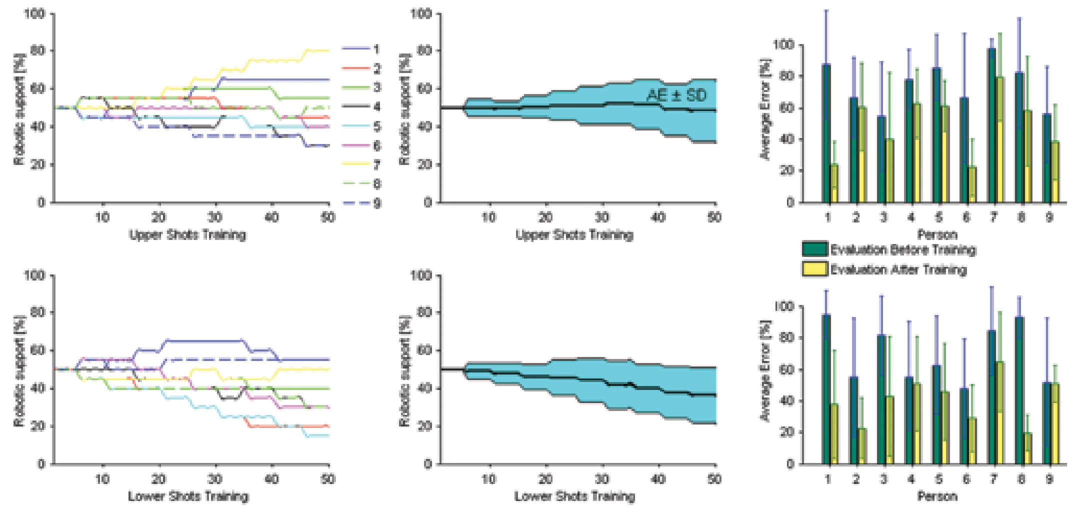



**Figure 6:** The curves of individual robotic assistance during training (left graphs), the average of curves of robotic assistance with corresponding standard deviation (middle graphs), and evaluation before/after training (right graphs) for Group 5 with HSA that changes the level of haptic support after five consecutive shots – Table 1c).

the individual performance before and after training session.

The results for Group 1 are shown in Figure 4. While it is clearly evident that there are many different and high varying support curves, all subjects, except subject 3 (upper shots evaluation) improved their motor performance. In the case of upper shots, subject 4 showed effective training, subjects 3, 5 and 7 showed a poor learning progress, while their support curves gradually increased and remained at high level by the end of training. At the beginning of the training session, subject 6 showed very poor performance, but eventually he learned those specific movements and his support curve decreased rapidly. The opposite example of successful learning was subject 5 in the case of lower shots. Subject 8 also showed poor learning in the case of lower shots, but in the case of upper shots he showed mostly good performance. Subjects 1, 7 and 9 showed good learning progress during lower shots training. All other subjects' learning curves were highly varied. The level of assistive robotic support ranged between 0 % and 100 % robot's stiffness.

The results for Group 2 are shown in Figure 5. Support curves varied considerably less than in Group 1 and they did not reach saturation. Most of the support curves varied in range between 0 % and 60 % of the robot's maximum stiffness. Subjects 5, 8 and 9 showed best performance in the case of both shots training. Their support curves decreased almost monotonically and at the end of training session they remained at less than 20 % of robotic support level. In upper shots training, the support curve of subject 7 decreased, but in the case of lower shots at the beginning of training it increased to 90 % and then monotonically decreased to the level of 40 % by the end of training (bottom left graph in Figure 5). Subjects, whose support curve reached the highest level of Group 2 at the end of training, were 3 (70 % in upper shots training) and 6 (80 % in lower shots training). Focusing on the training evaluations, all subjects have shown a successful motor learning progress. The only exception was subject 7, whose evaluations remained at approximately the same level (top right graph in Figure 5), but he had the lowest average error in the evaluation before training. Subjects 1, 4, 8 and 9 were the most outstanding, because they improved significantly.

The results for Group 5 are shown in Figure 6. Robotic support curves ranged between 15 % and 80 % and did not vary as much as in the first or the second group. The support curve of subject 7 increased monotonically during upper shots training and at the end of training it reached 80 %. On the other hand, subjects 5 and 9 (upper shots training) and subjects 2, 5 and 8 (lower shots training) had monotonically decreasing robotic support curves, but they did not drop below 15 %. If we look at the training evaluations, all subjects without exception have improved. The interesting case was subject 1 with the best improvement, but his support curve varied only in range from 50 % to 65 %. The opposite example was

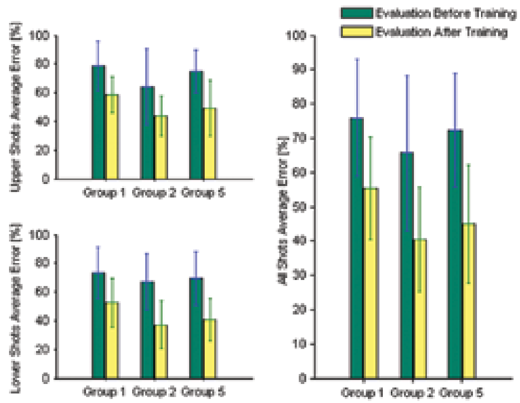



**Figure 7:** The training effect for all three groups, where each group contains the average of its subjects' evaluations. Left two graphs represent the performance of upper and lower shots separately, while right graph represents the performance of combined shots.

subject 8 with a significant improvement in lower shots training evaluations, where his support curve gradually decreased, but he reached only 30 % of robotic support.

All the individual evaluations before and after training were averaged within each of three groups. The upper shots average error was calculated separately from the lower shots as shown on the left graph of Figure 7. Statistical comparison between the upper and lower shots before training session (one-way ANOVA) did not reveal any statistically significant differences – Table 2. Therefore, we combined these shots and calculated the group average error (right graph in Figure 7) with corresponding standard deviation. Furthermore, one-way ANOVA analysis showed that evaluations before training session were not significantly different ($p = 0.266$) between all groups, but there

**Table 2:** Statistical comparison between upper and lower shots before training session

| Comparison | Before Training |
|---|---|
| Upper/Lower Shots | p = 0.629 |

was a significant difference between groups after training session ($p = 0.022$) – Table 3. All three groups improved significantly according to comparison between before and after training evaluation with $p$ less than *0.01* (one-way ANOVA). The improvement in Group 1 was 27.2 %, while Group 2 (with 38.4 %) and Group 5 (with 37.8 %) showed significantly better improvements – Table 4. Most importantly, we have also done a comparison between each of two groups after training evaluation. There was a statistically significant difference between Group 1 and Group 2 ($p = 0.006$), and near-statistically significant difference ($p = 0.063$) between Group 1 and Group 5. On the other hand, there were no statistically significant differences between Group 2 and Group 5 (one-way ANOVA, $p = 0.416$) – Table 5.

## Discussion

In this study we investigated the influence of three dynamically different HSA schemes on the outcome of learning of a rather demanding two-degrees-of-freedom motor task in three comparable groups of neurologically intact individuals. The determined support gain that dynamically changed on the basis of goal score stayed on the same level for every 1, 2 or 5 shot attempts, and then the decision was made by the controller either to decrease, increase or remain at the same level for the next 1, 2 or 5 shot attempt(s). On the basis of our preliminary experiments, we arbitrary chose to adapt the haptic support in steps of 5 %. This value was experimentally found not to be too small or too large. Too small support step might have similar effect as the third HSA, while too large step could lead to high oscillations (similar to the first HSA), where subject would feel a large marked difference of support change. This would also affect the learning curve. The step should be appropriate, so that the haptic support could be able to reach robot's stiffness limits in small number of shot attempts of the training session. While the task difficulty was exactly the same for all three groups the results show that the selection of the HSA that is appropriate for the given motor task has significant influence on the level of acquired motor skills after the training period. The results have demonstrated that in the group of subjects that learned the given motor task best (Group 2) the mean curve of haptic support exhibited monotonically falling characteristics, while in Group 1 the average haptic support curve remained approximately on a constant level. Group 5 that has shown better performance that Group 1 and slightly inferior performance as compared to Group 2 has also shown monotonically falling char-

Table 3: Statistical comparison between all groups during evaluation before and after training

| Comparison | Before Training | After Training |
|---|---|---|
| All groups | p = 0.267 | p = 0.022 |

Table 4: Statistical comparison of before versus after training evaluations within groups with the corresponding training improvements

| Comparison | Group 1 | Group 2 | Group 5 |
|---|---|---|---|
| Before/After Training | p < 0.01 | p < 0.01 | p < 0.01 |
| Improvement | 27.2 % | 38.4 % | 37.8 % |

acteristic of average haptic support curve. According to the results of this study, which show a significant improvement in task-specific motor learning of all three groups on average, we can conclude that the HSA implemented in Group 1 is not as appropriate as the other two, because it does not allow the individual to explore the training task at the current level of support, which in our opinion is one of the crucial aspects of motor learning. It turned out that changing the support level after each shot attempt leads to learning fluctuation, but by changing the support level after more than five shot attempts the training effect to motor learning is slower. This can be seen through the support curves and the differences between both evaluations. The support curves in the second and third group did not vary as much as in the first group, where support curves were oscillatory. Furthermore, a decreasing support curve with an increasing number of task repetitions is very likely a good and important indicator of effective motor learning. Based on these arguments and the results of statistical analysis, we can also conclude that the first HSA – Group 1 has not been tuned with the participants of the first group in general. Statistical analysis also revealed that there was no significant difference between participants' performances of all three groups before training, while there was a significant difference after training. One group was able to learn faster than the other, but according to significant improvements, almost all participants learned those specific movements in order to achieve as many goals as possible. There can be several other aspects, which also ensure successful training, such as visual guidance and score. Visual guidance (reference player) was useful to carry out the current movement, but nevertheless all three groups had the same protocol rules. Another aspect is more psychological in nature. During the experiment, every participant could see his score and the accuracy of goals achieved. For some participants it was a bit stressful whether they could achieve any goals or not. This was not necessarily a negative factor, even more, it promoted a challenge.

Table 5: Statistical comparison among groups after training session

| Comparison | Differences |
|---|---|
| Group 1 / Group 2 | p = 0.006 |
| Group 1 / Group 5 | p = 0.063 |
| Group 2 / Group 5 | p = 0.416 |

Our results suggest that for every motor task or, equivalently, for every motor ability of a particular subject such a HSA scheme must be implemented that maximizes training effects in a limited number of training attempts. This has great implications for movement training in post-stroke individuals that have very different movement abilities as well as recovery potential. These two features of each individual may be systematically explored through observation of the average haptic support curve characteristics that result as a consequence of utilization of a particular HSA scheme in a selected number of training attempts. In this way, an optimal HSA scheme may be experimentally determined.

## Conclusions

The results of this study provide a new insights on performance-based HSA schemes for optimal motor learning to particular training dynamics. It indicates an importance of factor "when to change" the robotic support and not only "to what extent to change". We assume that each individual has their own way of learning and the motor training algorithms should monitor their current abilities. Furthermore, based on the results of this study, we could develop the adaptive haptic support algorithm, that would adjust the algorithm dynamics according to current support curve. This means that if current support curve becomes too oscillatory, the time of changing haptic support should be increased, and vice versa. Although, the experiment was limited to the healthy population with a short period of treatment time (one training session for each subject), certain main outcomes should be considered and incorporated in further research of dynamic algorithms for stroke patients to provide the appropriate robotic support during movement training.

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