GENTLE/A - Adaptive robotic assistance for upper-limb rehabilitation

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Submitted to the University of Hertfordshire in partial fulfilment of the requirements of the degree of Doctor of Philosophy

July 2013

Acknowledgements

I would like to express gratitude to my principal supervisor Dr. Farshid Amirabdollahian for his advice and constant encouragement throughout this research. I express my appreciation for the guidance that he offered towards the implementation, testing and statistical evaluation of my studies. I personally thank Farshid for the flexibility that I enjoyed during this PhD balancing my working hours to suit the school terms of my two children.

I would like to thank my secondary supervisor Prof. Kerstin Dautenhahn for her constant support during my PhD and her valuable feedback on all my publications and the thesis drafts.

Thanks to everyone in Adaptive Systems Research Group and in particular, Michael Bowler, Dr. Angelo Basteris, Nauman Shah and more for their help in various phases of my research. Special thanks to ladies in the Research office for being very friendly and guiding me through university's processes. Also, I like to thank all the participants who took part in my studies for their valuable time and feedback. Many thanks go to all my friends in St Albans for their warm support.

I am particularly grateful to my two lovely children, Pranav and Moukthika and my dear husband, Chandra for all their love and patience. I can hardly imagine getting to this stage of my research without their support and encouragement.

Sincere thanks to the SCRIPT project for providing a studentship to support myself during the extension period of my PhD. The work reported in this thesis was supported by a research studentship from School of Computer Science, University of Hertfordshire.

Abstract

Advanced devices that can assist the therapists to offer rehabilitation are in high demand with the growing rehabilitation needs. The primary requirement from such rehabilitative devices is to reduce the therapist monitoring time. If the training device can autonomously adapt to the performance of the user, it can make the rehabilitation partly self-manageable. Therefore the main goal of our research is to investigate how to make a rehabilitation system more adaptable.

The strategy we followed to augment the adaptability of the GENTLE/A robotic system was to (i) identify the parameters that inform about the contribution of the user/robot during a human-robot interaction session and (ii) use these parameters as performance indicators to adapt the system. Three main studies were conducted with healthy participants during the course of this PhD. The first study identified that the difference between the position coordinates recorded by the robot and the reference trajectory position coordinates indicated the leading/lagging status of the user with respect to the robot. Using the lead-lag model we proposed two strategies to enhance the adaptability of the system. The first adaptability strategy tuned the performance time to suit the user's requirements (second study). The second adaptability strategy tuned the task difficulty level based on the user's leading or lagging status (third study).

In summary the research undertaken during this PhD successfully enhanced the adaptability of the GENTLE/A system. The adaptability strategies evaluated were designed to suit various stages of recovery. Apart from potential use for remote assessment of patients, the work presented in this thesis is applicable in many areas of human-robot interaction research where a robot and human are involved in physical interaction.

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Chapter 1

Introduction

The use of robotic devices to offer rehabilitation training is a relatively new field within the area of robotics in health care and emerged from the idea of using robots to assist people with disabilities. Rehabilitation robotics is rapidly advancing based on the developments in robotics, haptic interfaces and virtual reality (Harwin et al., 2006). The idea of using robots to assist a therapist with a rehabilitation exercise has led to the development of several rehabilitation robotic devices. Considering the robot as an advanced exercise-tool under the therapist's supervision, the key challenge in the area of rehabilitation robotics is how best the therapist's skills can be enhanced with the advancing robot technology. The robotic devices are capable of not only offering more frequent and more accessible therapies but also providing new insights into treatment effectiveness based on their ability to measure interaction parameters. The focus of this PhD is therefore on auto-tuning robotic assistance in upper-limb rehabilitation based on the performance of the user.

According to the World Health Organisation's (WHO) statistics (WHO, 2012) the average life expectancy of the world's population is increasing consistently. With an increasingly ageing population, the burden of disease on the economies of many countries is also increasing. Stroke, being one of the leading causes of disabilities in many countries, is leaving a considerably large number of people to live with its consequences. The incidence of stroke increases with age and estimates show there will be a marked increase in the number of stroke events in EU countries from approximately 1.1 million per year in 2000 to 1.5 million per year in 2025 (Truelsen et al., 2006).

Rehabilitation is a restorative process by which patients with strokes undergo treatment to help them return to normal life by regaining and relearning the skills of everyday living (Kwakkel et al., 2004). It also aims at helping the survivor to understand and adapt to difficulties, prevent secondary complications and educate family members to play a supporting role. The scope of stroke recovery spans very wide, recovery can start as early as in the sub-acute stage (immediately after the incidence of stroke) and can extend into the chronic stages too (six months post stroke) (Gresham et al., 2004). Early intervention is believed to be effective on the quality of rehabilitation (Krakauer, 2006). The primary focus of post-stroke rehabilitation during the inpatient phase is on gait rehabilitation. Upper extremity is often neglected during the early stages when there is a better chance for recovery. Therefore stroke sufferers with functional impairments often do not reach the full potential for recovery in their upper extremity when discharged from inpatient settings (Duncan et al., 2003; Malouin, 2005; Broeks et al., 1999). The major hurdle in offering rehabilitation to stroke sufferers is the lack of sufficiently trained personnel (Hoenig et al., 2006). *One of the potential solutions could be providing the existing personnel with advanced tools that can reduce the monitoring time without any compromise on the impact of the treatment.*

Recovery is largely variable between patients in every stage of post-stroke rehabilitation and hence it is necessary that the rehabilitation techniques need to be geared towards patients' specific motor deficits. The review conducted by Timmermans et al., 2009 focussed on identifying the criteria to develop optimal upper-limb rehabilitation technology and concluded that 'A major challenge for rehabilitation technologies is to provide engaging patient-tailored task oriented arm-hand training in natural environments with patient-tailored feedback to support (re)learning of motor skills'. Reviews of previous upper-limb post-stroke rehabilitation studies (Kwakkel et al., 2008; Mehrholz et al., 2009; Prange et al., 2006) involving a robotic-assistance, summarized that (i) robot-aided rehabilitation offered no significant improvement in Activities of Daily Living (ADL) when compared to conventional rehabilitation, however, (ii) motor strength and motor function can improve with robot-aided rehabilitation techniques and (iii) robotic therapy will have the greatest impact if it can motivate the patients to exercise independently and thereby reduce the role of the therapist without the loss of treatment's effectiveness. *This further emphasizes the need for robotic therapy to be highly adaptable according to the specific needs and performance of the patient.*

Robots also have the capability to track many bio-mechanical parameters of the user during a human-robot interaction (HRI) session. Studies (Reinkensmeyer et al., 2000; Kahn et al., 2006) highlighted that the data capturing capability of the rehabilitation robotic devices could provide feedback to the therapists at a greater frequency (after every therapy session) and allow them to tailor the therapy more frequently, but this area lacks further research. The feedback recorded when presented at run-time to the patient during a HRI session could also prompt for auto-correction of errors.

The brief background presented in this section and the literature review presented in Chapter 2 bring to attention that the lack of evidence of usefulness of the robotic therapy when compared to the conventional therapy is one of the key reasons for low uptake of rehabilitation robotics. Other reasons like cost-effectiveness of the robot-assisted rehabilitation programmes, affordability and safety of robotic devices for in-home rehabilitation were also widely discussed in the literature. *It was also identified that the data capturing capability of the robotic devices can offer performance feedback to tailor the rehabilitation training.* The robotic devices are capable of recording parameters like time taken, speed, force used to reach the target which can offer good insights into the performance of the user interacting with the rehabilitation system. Taking these ideas further several research groups studied performance-based rehabilitation techniques ever since it was first proposed as ‘progressive robot-assisted training’ by Krebs et al (Krebs et al., 2003). Researchers used various techniques to assess the patient’s performance and thereby alter the guidance offered by the robot. Results from similar studies (Krebs et al., 2003; Johnson et al., 2005; Lo et al., 2009) suggested that ‘assist as needed’ approach is more effective when compared to always assisting with a fixed amount. Studies by Colombo et al (Panaresse et al., 2012; Colombo et al., 2012) informed that robot-aided training will be more effective when it is progressive as well as challenging according to the patient’s ability.

The primary goal of our[a] research with the GENTLE/A rehabilitation system was to identify the parameters (performance indicators) that can inform the contribution of the participant during a HRI session. The lead-lag model that we proposed during this research is a mechanism that could inform the performance of the user during a HRI session and also has the potential to provide insights into the recovery progress over a period of time in a rehabilitation setting.

Our next aim was to enhance the adaptability of the system based on the performance indicators identified by the lead-lag model. We developed adaptability strategies that autotuned the robotic assistance/resistance based on the performance contributions of the user identified using lead-lag model. From a clinical perspective 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 progresses. We therefore believed that the adaptability of the training should be based both on the performance and on the post-stroke recovery stage of the participant. Hence we focussed on identifying the adaptability strategies that would tune the system to respond according to

[a] ‘Our’, ‘We’ and similar words suggesting a group or team are only used out of stylistic reasons. All the work presented in this thesis was carried out by the author.

the requirements of the user (suitable for initial stages of post-stroke recovery) and that would alter the challenge in the task (suitable for later stages of recovery). Additionally, we anticipate that in clinical settings, the scope of the performance indicators gathered over a block of therapy sessions, could be extended as assessment parameters. The assessment parameters could not only inform about the recovery process of the patient but also aid in automatically adjusting the adaptability strategy followed by the system.

1.1 Research Questions

RQ1: Can the contribution of the user/robot be identified during a HRI session with the GENTLE/A rehabilitation system?

RQ2: Can this identification of contribution be further utilised as a performance indicator?

RQ3: How can the performance indicators be used to improve the adaptability of the GENTLE/A rehabilitation system?

The background research highlights that the future of the technology assisting rehabilitation lies not in mimicking the conventional rehabilitation techniques but in offering the therapists what would otherwise incur additional cost and time when following a conventional therapy route. Further investigations in these lines, considering robots as advanced rehabilitation devices, identified that the stream of patient data that the robots capture during the therapy sessions could be a potentially rich resource informing the therapists about the patient's recovery. In this context we believed that this feature could also be used to identify the performance of the user and auto-adapt the system's response based on the identified performance. We therefore formulated the research questions listed above that we believe would allow us to develop an enhanced adaptive interface to the GENTLE/A rehabilitation system.

Three main studies were conducted with healthy participants during the course of this PhD. The first study aimed to identify the contribution of the user/robot during a HRI session using the lead-lag model (RQ1). The second study tested the usefulness of the parameters identified by the lead-lag model as performance indicators (RQ2). The adaptive algorithms developed using these performance indicators were evaluated during the second and the third studies (RQ3).

1.2 Methodology

The GENTLE/A rehabilitation system is a successor of the GENTLE/S rehabilitation system (Coote et al., 2008; Amirabdollahian et al., 2007; Loureiro et al., 2003; Harwin et al., 2001) that used haptic and virtual reality technologies to deliver challenging and meaningful therapies to upper-limb impaired stroke patients. The GENTLE/S system used the HapticMaster robot (HM) as the rehabilitation robotic device and offered a range of therapy activities to suit various stages of post-stroke recovery. The system provided four different levels of 'active feedback': visual (through the Graphical User Interface), haptic (through the crisp haptic sensation provided by the HM), auditory and performance cues. The GENTLE/A system retains these major features of the GENTLE/S system while significant modifications were carried out by the author to suit the new system requirements. These modifications required some hardware and software reconfigurations and are detailed in Chapter 3.

The HM was programmed to follow Minimum Jerk Trajectory (MJT) (Amirabdollahian et al., 2002) that mimics human arm movements to execute simple point-to-point reaching tasks. In order to evaluate the user's contribution interacting with the robotic device, the strategy followed during this PhD was to compare the robot recorded positions with the MJT positions. This informed whether the user was leading or lagging the performance at any given point in time, and this information was used to adapt the system's behaviour accordingly.

Research (Morasso, 1981; Abend et al., 1982; Flash et al., 1985) demonstrated that human arm movement has a straight line path with a single peak and bell shaped velocity profile. Different approaches (Wolpert et al., 1995) were proposed to mimic human arm movements, minimum jerk is one such model which is simple to implement but with a limitation of applicability with straight-line paths. The adaptability strategies proposed and evaluated during this PhD could be tested on any rehabilitation system that uses reference trajectory to guide movement training along straight line paths.

Three main studies were conducted with healthy participants during the course of this PhD and each main study was preceded by a pilot study with limited number of participants, in order to first evaluate the performance of the technique/algorithm implemented on the system. Ethical approval was obtained at every stage to conduct either a pilot study or a main study from the University of Hertfordshire's ethical committee to recruit healthy participants in the study. The participants were briefed about the experimental protocol before giving their consent to take part in the study.

The Virtual Reality (VR) environment was developed using OpenGL and program code was developed in C++ using Visual Studio 9.0. Data was logged into text files during the experimental sessions. Microsoft Excel 2010, IBM SPSS 21, MATLAB 7.0 and Strawberry Perl 5.10.1.5 were extensively used to statistically analyse the generated data and plot the figures and graphs. The findings and feedback obtained from every study provided direction for further investigations and guided the design and aims of subsequent studies.

1.3 Contribution to knowledge

This research focussed on innovative strategies to initially identify human contributions in interaction and later enhance the adaptability of a robotic rehabilitation system for upper-limb impairments. The primary goal of this research was to develop a novel technique to identify the contributions of a user and a robot during an interactive session and use this information to adapt the behaviour of the system. Performance based robot-assisted training has been implemented and tested by several research groups on various robotic devices and platforms for stroke rehabilitation. These studies (Emken et al., 2005; Krebs et al., 2008; Lo et al., 2009; Casadio et al., 2009) highlight 'assist as needed' as an effective approach for performance based training.

During this research we aimed to develop a training algorithm that could identify the contribution of a user and adapt the assistance/resistance offered by the system based on the lagging/leading performance of the user. We believe that the approach and methodology developed would be applicable to clinical settings and could be easily adapted to various robotic platforms.

Additionally, the studies conducted during this PhD carried out investigations to test the performance of the users in a completely virtual environment (virtual targets on the screen) vs an embedded environment (both real and virtual targets). These investigations could contribute to bridge the gap between the training in a rehabilitation setting and application of the skill learnt in a real life situation. Moreover, the performance indicators identified during this research, could be potentially used as assessment parameters in long-term clinical trials informing the therapists about the recovery progress over a period of training sessions.

The work presented in this thesis is applicable in research areas like rehabilitation robotics, assistive technologies, upper-limb bio-mechanics and related fields.

1.4 Thesis layout

This chapter briefly introduced the subject area and the motivation behind the research presented in this thesis. The chapter also highlighted the research questions that will be addressed in the next chapters, listed the contribution to knowledge and the methodology used during this PhD.

Chapter 2: Describes the background literature that is relevant to this research. The chapter presents stroke statistics, stroke rehabilitation and the need to augment the process of rehabilitation both in terms of quality and intensity. The chapter then briefly discusses the role of robotics in healthcare, primarily focussing on need for robots in rehabilitation which is the research area of this PhD. The attention is then drawn to the areas in which the robotic rehabilitation devices can augment the role of a therapist and the progress already achieved in this direction is discussed. The chapter finally highlights 'adaptability' of the rehabilitative training as one of the key areas that needs further investigations in the area of rehabilitation robotics.

Chapter 3: Presents the initial investigations carried out during a pilot study and a subsequent main study. The parameter recording capability of robot sensors is a potential indicator of the performance of the user interacting with the robotic device. Performance feedback not only offers insights into the recovery progress but also helps in tailoring the rehabilitative training according to the user's requirements. The studies presented in this chapter aimed to identify the parameters that could inform the performance of the user interacting with the system. Comparing the robot recorded positional data with the reference trajectory positions could successfully inform the leading/lagging performance of the user interacting with the system.

Chapter 4: The performance indicators identified by the first two studies were used to develop an adaptive algorithm that could tune the duration given to execute point-to-point movements based on the performance of the user. This adaptability strategy is thought to be more suitable to the initial stages of post-stroke recovery where the patient might need more assistance from the system and lot of motivation to train more. This chapter presents the study conducted to evaluate the performance of the adaptive algorithm. The results showed that the adaptive algorithm could successfully tune the duration to execute point-to-point movements to a user-specific optimum value. The results also identified that the input conditions imposed during various point-to-point movements executed during the study, influenced the performance of the user. The possible reasons for the influence were examined and further enhancements to the adaptive algorithm were discussed.

Chapter 5: In rehabilitation setting, as the recovery progresses over a period of time the task is made progressively challenging by the therapist. In order to address this requirement we proposed a complementary adaptability strategy. The second adaptive algorithm tuned the task difficulty level based on the user's leading status. The pilot study and a subsequent main study conducted to evaluate the adaptive algorithm-II was described in this chapter. The results from these studies showed that the system could successfully scale up/down the difficulty level of the task based on the user's performance. The questionnaire responses informed that the participants could perceive a change in the difficulty level of the task during the experimental session. In addition, further enhancements to the adaptive algorithm and its applicability in the rehabilitation settings were also discussed in this chapter.

Chapter 6: Summarises the findings from all the studies conducted during this PhD. The chapter revisits the research questions and the contribution to knowledge presented in Chapter 1 and reviews the ways in which they were addressed during the course of this

PhD.

Chapter 7: Concludes the thesis, lists the limitations of the research conducted, outlines future directions and possible applications in future studies.

1.5 Publications list

The work reported in this thesis contributed to publications listed below which include three peer-reviewed international conference papers, a journal article (revised manuscript submitted for second review) and a poster presented at a workshop. The first author of these articles conducted the research studies and produced a first complete draft of the articles. The co-authors guided and supported during the design, development and evaluation process of the studies and also provided feedback on the drafts of the articles. The reference to each article in the list below is followed by a brief description of its relationship with this thesis.

1. Chemuturi R, Amirabdollahian F, Dautenhahn K: A study to understand lead-lag performance of subject vs rehabilitation system. In *Proceedings of ACM 3rd Augmented Human International Conference: 8-9 March 2012; Megéve, France; AH'12: article(3).*

   This paper reports the results from the preliminary study conducted to explore the usefulness of the 'position data' presented in Chapter 3.

2. Chemuturi R, Amirabdollahian F, Dautenhahn K: GENTLE/A: Adaptive Robotic assistance in Stroke Rehabilitation. *Poster presented as part of COST European Network Conference & Exhibition: 19 March, 2012; Southampton, UK.*

   This poster presents a summary of first two studies conducted during this PhD that are reported in Chapter 3.

3. Chemuturi R, Amirabdollahian F, Dautenhahn K: Impact of lead-lag contributions of subject on adaptability of the GENTLE/A system: an exploratory study. In *Proceedings of IEEE RAS/EMBS 4th International Conference on Biomedical Robotics and Biomechatronics (BioRob): 24-27 June, 2012; Roma, Italy; BioRob 2012:1404-1409*.

   This paper presents the 'transition to vector space' reported in Chapter 3.

4. Chemuturi R, Amirabdollahian F, Dautenhahn K: Adaptive training algorithm for robot-assisted upper-arm rehabilitation, applicable to individualised and therapeutic human-robot interaction. *Journal of NeuroEngineering and Rehabilitation 10.1 (2013): 102*.

   This journal article presents the results from the study conducted to evaluate 'Adaptive algorithm-I' reported in Chapter 4.

5. Chemuturi R, Amirabdollahian F, Dautenhahn K: Performance based upper extremity training: a pilot study evaluation with the GENTLE/A rehabilitation system. In *Proceedings of IEEE 13th International Conference on Rehabilitation Robotics (ICORR): 24-26 June, 2013; Seattle, Washington USA*.

   This paper presents results from a pilot study to evaluate 'Adaptive algorithm-II' reported in Chapter 5.

Chapter 2

Background

2.1 Stroke and its effects

Several neurological disorders such as cerebral palsy, multiple sclerosis, cerebro vascular accident (stroke), spinal cord injury (SCI),etc., can lead to impairments in upper-limbs. Stroke (NSA, 2013; Swaffield, 1996; Wade, 1988) is one of the leading causes of chronic impairments in upper-limbs that might affect many activities of daily living. A stroke occurs when there is an interruption to the blood flow to a part of the brain. This interruption of blood flow can happen in two different ways: (i) when a blood clot develops in an artery carrying blood to the brain (ischemia) and (ii) when an artery bursts and blood bleeds in the brain (hemorrhage). The brain cells die due to the lack of oxygen caused by the interruption in blood flow and brain damage occurs. The motor functions controlled by the damaged part of the brain are lost and result in impairments.

Effects of stroke

Depending on the location and the extent of the brain damage stroke can result in various impairments related to speech, movement and memory. Listed below are some of the deficits endured by stroke sufferers (HealthCare Research & Quality, 1995; Kwakkel et al., 1999; NSA, 2013).

- *Speech*
    - ∗ Aphasia: Inability to speak or understand language.
- *Movement*
    - ∗ Hemiparesis: Paralysis of one side of the body contra-lateral to the damaged area in the brain.
    - ∗ Spasticity: Uncontrollable muscle tightness in an arm or leg that can cause pain and affect movement.
    - ∗ Apraxia: Altered voluntary movements.
    - ∗ Hemi-neglect: Neuropsychological condition in which, after damage to one hemisphere of the brain, a deficit in attention to and awareness of one side of space is observed.
- *Memory*
    - ∗ Agnosia: Patient's inability to recognise shapes, objects or persons.
    - ∗ Memory loss.
    - ∗ Memory deficits.
- *Visual deficits*
- *Depression*

2.2 Need for rehabilitation

Stroke mortality has decreased in the recent years due to improved care immediately after the incidence of the stroke and early and more accurate diagnosis, but about 40% of stroke survivors experience moderate to severe impairments that require special care (Gresham et al., 2004). Among various impairments, hemiparesis is prominent in three-quarters of stroke survivors (Gresham et al., 2004; NSA, 2013). Based on the time elapsed after the incidence of stroke, patients may be classified as being in sub-acute (initial weeks), acute (between few weeks and six months) or chronic (past six months) stage. In spite of many advances in brain research, a lot of things are still unclear about self-repairing mechanisms of brain after stroke but evidence (Krakauer, 2006) shows that there is a greater scope for recovery in sub-acute and acute stages. Brain repair could occur either through reorganisation, where the same muscles are used to accomplish a motor function as before the damage, or through compensation, where a different part of the brain takes over and a different set of muscles are recruited to achieve the motor task (Nudo, 2007; Richards et al., 2008). Whether the recovery happens through reorganisation or through compensation, learning is a necessary condition. This process of (re)learning the lost motor skills is termed as *rehabilitation*.

Rehabilitation is a restorative process that helps the stroke survivors to regain functional independence and resume self-care activities as much as possible (Kwakkel et al., 2004). It also aims at helping the survivor to understand and adapt to difficulties, prevent secondary complications and educate family members to play a supporting role. Post-stroke rehabilitation could begin as early as in the sub-acute stage once the life-threatening problems are under control and the patient's condition is stable. The scope of stroke recovery could also extend well into the chronic stages. Early interventions during sub-acute and acute phases for durations suitable to patient's condition and repetitive training are believed to be more effective, (Hendricks et al., 2002; Kahn et al., 2006).

Stroke rehabilitation usually begins in the inpatient settings like hospitals and proceeds to outpatient facilities as the recovery progresses. The advantage of inpatient rehabilitation settings is, intensive and comprehensive training could be offered in sub-acute stage.

Outpatient settings are more suitable for acute and chronic stages. It is estimated that the majority of the stroke care costs are related to hospital inpatient services (Ömer et al., 2009). Hence inpatient stays are restricted to few weeks and recovery to the full potential is often not reached when the patients are discharge to outpatient settings. Outpatient rehabilitation is accompanied by a disadvantage of physical distance between the patient's home and the outpatient clinic. The clinical decisions also depend on the knowledge and experience of the therapist (Langhorne et al., 2009) which could become a potential hurdle given the increasing incidence of stroke (WHO, 2012).

2.3 Need for robotics in rehabilitation

Neurological disorders such as stroke, cerebral palsy, etc., can lead to physical, mental as well as cognitive impairments. Patients need to undergo rehabilitation to restore both their physical and social well-being. The process of rehabilitation, especially the one involving physical impairments, is physically very demanding for therapists and is a continuous and long process. For example, to train a patient with lower-limb impairments it often requires a team of therapists to offer manual assistance when needed. Alongside the experience, therapists also require good skill and training in order to assess the recovery progress. (*Reason 1: augment the therapists' skills with advanced technology that can not only offer physical assistance but also provide performance feedback*)

With the increase in ageing population (United Nations, 2013; WHO, 2012), the incidence of neurological illnesses leading to impairments is predicted to increase in the coming years. This might mean that the rate of growth of the population with rehabilitation needs might be way higher than the rate of increase in the number of therapists to offer rehabilitation. (*Reason 2: address the rapidly growing rehabilitation needs*)

The process and duration of rehabilitation is patient and impairment specific. Current rehabilitation programmes in many countries do offer essential rehabilitation (like gait rehabilitation) in inpatient settings, but as the inpatient stays are considered to be very cost intensive, they are kept to a minimum. Not many patients would reach to a full scope of recovery with the minimised hospital stays. Intensive and repetitive training in the early stages of recovery is deemed to be effective (Krakauer, 2006), which could be made possible by electromechanical training devices like robots. Such devices can offer training according to the patient's demand without being effected by time/physical strain/boredom when compared to a human therapist. Furthermore, outpatient rehabilitation encounters various other hurdles such as the physical distance between the patient's home and the rehabilitation clinic. Advanced technology can offer a solution in the form of home-based rehabilitation at the convenience of patient's home and free-time. (*Reason 3: increase the intensity of rehabilitation in early stages of recovery with a scope of tele-rehabilitation in later stages of recovery*).

The robotic technology is successfully utilised to develop assistive robotic devices to help people overcome the disabilities and regain independent living. Smart wheelchairs that avoid obstacles and intelligent arm attachments to wheelchairs to assist in activities of daily living are already available as commercial devices in the market. This inspired researchers to investigate the applicability of robotics to rehabilitation (*Reason 4: successful application of robotics in contemporary fields like assistive technology*)

2.4 Robotics in health-care

Robotics was identified as an enabling technology with a capability to provide various solutions in healthcare. Robotics for Healthcare (R4H) (Butter et al., 2008), a European Commission study explored the potential of robotics in healthcare. The definition of robotics in healthcare used by R4H was

"Robotics for Medicine and Healthcare is considered the domain of systems able to perform coordinated mechatronic actions (force or movement exertions) on the basis of processing of information acquired through sensor technology, with the aim to support the functioning of impaired individuals, medical interventions, care and rehabilitation of patients and also to support individuals in prevention programmes."

According to the various activities (see R4H value chain Figure 2.1) involved in the diverse domain of healthcare, five broad areas with potential benefits from robotics were identified (see Figure 2.2).

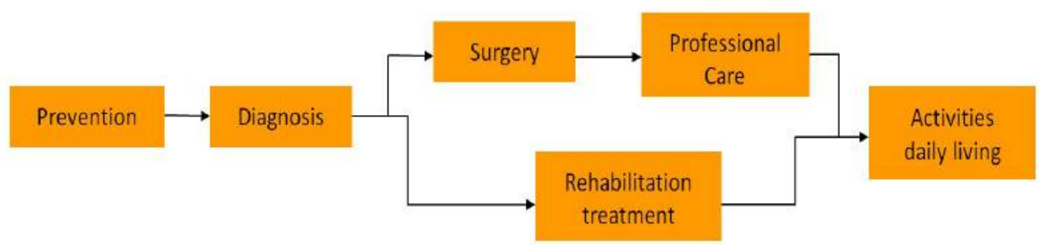


Figure 2.1: Activities in the R4H value chain. Image courtesy Ir. M Butter, Senior Researcher and Consultant, TNO

Robotics for health-care is a special branch of robotics which focuses on robotic devices that can be used to help people recover from physical disabilities and restore their independent living. It can be classified into five broad categories (see Figure 2.2) which are described briefly in the following subsections.

2.4.1 Robotics for medical interventions

One of the active applications of robotics among various medical interventions is surgery. Robotically assisted surgery is contributing to overcome both the limitations of minimally invasive surgery and to enhance the capabilities of the surgeon performing an open surgery. Minimal invasion reduces the trauma that the patients undergo during the surgery, lessens the scar due to incision, shortens hospital stays and speeds up the post-surgical recovery

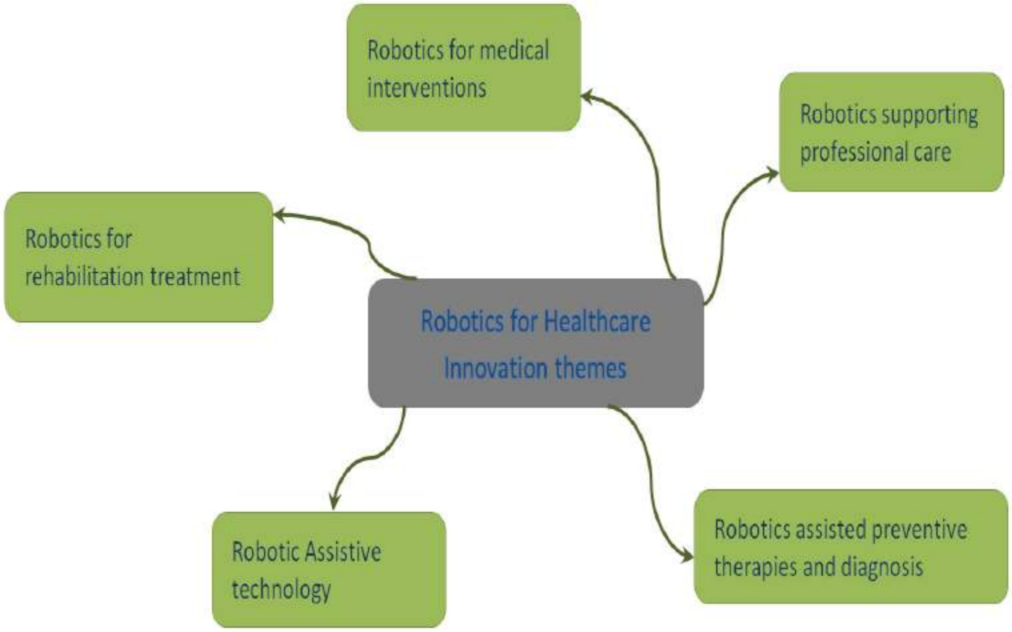


Figure 2.2: Innovation themes of R4H. Image courtesy Ir. M Butter, Senior Researcher and Consultant, TNO (Contact author of R4H final report)

process. Da Vinci surgical system (see figure 2.3a) (IntuitiveSurgical, 2013; Ballantyne et al., 2003) can facilitate a minimally invasive alternative not only for surgeries needing large, traumatic incisions but also for laparoscopic surgeries. It offers more dexterity to the surgeons to reach confined parts of the human body. CyberKnife (see Figure 2.3b) (Accuray, 2013; J Adler Jr et al., 1997) is a surgical robotic system used by the oncologists to treat tumours. The robotic arm of CyberKnife directs the pencil beams of radiation accurately on to the tumour without damaging the surrounding areas. RUMI laparoscopic manipulator (see Figure 2.3c) (CooperSurgical, 2013; Koh, 1998) for pelvic surgery allows superior exposure and access to the surgeon to an otherwise contained space. The many attachments to the RUMI device also facilitate varying patient anatomy. With the miniaturisation of sensor and other related technologies are evolving *smart medical capsules*. At present the applicability of these intelligent medical capsules is being researched in diagnosis, targeted drug delivery and surgery (Chandrasekharan, 2013). Endoscopic capsules (Xie et al., 2006) with inbuilt sensors and cameras are already available in the market. The new functionalities that are being investigated are drug delivering capsule devices and surgical capsules to accomplish small surgical procedures such as biopsy (Kong et al., 2005).

(a) Da Vinci Surgical System. ©2013 Intuitive Surgical Inc.

(b) CyberKnife System ©2013 Accuray Inc.

(c) RUMI laparascopic manipulator ©2013 CooperSurgical Inc.

Figure 2.3: Surgical robotic systems

2.4.2 Robotics for professional care

Providing care to patients at home, in hospitals, in care homes and similar places has an ever growing demand. Robotic applications to assist the care givers while rendering professional care are already into the healthcare system. RoboWard (Figure 2.4a) (RoboPharma, 2013; Clin, 2013) is a standalone drug dispensing system that was designed to minimise the administrative work carried out by the nursing staff in busy nursing home environments. It can make the dispensing of dangerous and/or expensive medicines safe and reliable preventing any misuse. Robots in home for patient monitoring or acting as companions are also becoming popular with the increase in the ageing population. Care-O-bot (see Figure 2.4b) (Graf et al., 2009; Parlitz et al., 2008) is a designed as a mobile service robot that monitors and helps the patients with their daily routine activities. Sunflower robot (see Figure 2.4c) (Syrdal et al., 2011; Koay et al., 2013) designed by our colleagues at University of Hertfordshire acts a robotic home companion offering physical and cognitive assistance. Sunflower can assist in physical activities like fetching and carrying, etc., can notify the user of completion of tasks/activities. It can also alert the user about critical tasks like daily intake of medicines, doctors appointments, etc.

(a) RoboWard
©2013 RoboPharma B.V.

(b) Care-O-bot
Image courtesy Fraunhofer IPA

(c) Sunflower
Image courtesy Dr Kheng Lee Koay

Figure 2.4: Professional care robots

2.4.3 Robotics for assistive technology

Robotic devices offering the opportunity to improve the independence of people with disabilities and facilitating their social and professional integration by assisting them in performing Activities of Daily Living (ADL) fall under Assistive Robotic Technology (AT). Robotised systems are successfully being used to support both mobility and manipulation. Smart wheelchairs (Simpson, 2005) improve the manoeuvrability on difficult terrain and avoid obstacle collision. Handy 1 (Topping, 2002) was a low-cost commercially available device that helped severely disabled in ADL like eating, drinking, teeth cleaning, shaving and also make-up application. MULOS (Motorized Upper Limb Orthotic System) (Johnson et al., 2001) is a sophisticated upper-limb orthosis providing controlled movements to the severely disabled. The system was designed to operate under three modes of control 'assistive mode' to work as an assistive device, 'passive mode' to offer therapy to joints after injury, 'exercise mode' to provide strengthening exercises for specified joints. Hence MULOS is considered as both assistive and rehabilitation robotic device. iARM (see Figure 2.5) (AssistiveInnovations, 2013; ExactDynamics, 2013), formerly known as MANUS (Driessen et al., 2001) is a wheelchair attachment that can contribute to the independence in living for severely disabled. The attachment comes with an added advantage of being neatly folded away when not in use. iARM can help the disabled to resume social activities like having a drink with friends, taking the dog for a walk, shopping in the supermarket, etc. and promotes integration into the community.

Figure 2.5: iARM (intelligent Assistant Robot Manipulator)
Image courtesy Assistive Innovations bv and Exact Dynamics

2.4.4 Robotics for assessment and diagnostics

Preventive and predictive procedures are the initial stages in healthcare programs and when administered properly would identify illnesses in earlier stages. This early detection would reduce the risk for the patient and also lower the healthcare costs. Predictive procedures involve identifying the groups at risk and carrying on screening procedures at regular intervals. The robotic systems with their inbuilt sensors have the capability to monitor individual patient progress and can therefore facilitate individual assessment in a large population of risk group. Endoscopic micro-capsules (Karagozler et al., 2006) were designed to diagnose digestive track diseases. These micro-capsules ease the discomfort the patient undergoes during an otherwise complicated process of endoscopy. The miniaturization of sensor technology is leading to further miniaturization of these smart medical capsules which now come with improved motion control and cameras. Intelligent fitness systems (Barton et al., 2006; PoPe-TuDelft.com, 2013) assessing the fitness level of the population of users is another application of robotics in this area. Given the capability of the sensors to capture many bio-mechanical parameters of the user, robotic systems could offer a rich source of feedback for assessment and diagnostics. Despite the potential applicability not many commercial robotic systems are available in this area and it needs further research.

2.4.5 Robotics for rehabilitation

Rehabilitation is a process or treatment to restore physical, mental and cognitive impairments. Robots are being extensively used as advanced tools to offer rehabilitation treatments. Robotic systems that could assist the treatment of physical impairments and also cognitive and mental impairments have been designed and successfully tested. Kaspar (Dautenhahn et al., 2009; Robins et al., 2009), a humanoid robot (see Figure 2.6), designed and developed by our colleagues at University of Hertfordshire helps to develop and maintain social skills in children with autism. Kaspar plays the role of an interactive toy and helps with cognitive development of children suffering with autistic spectrum disorders (ASD). The studies with Kaspar revealed that children with autism in general respond very positively to Kaspar and find the interaction with Kaspar non-threatening and enjoyable.

Rehabilitation robotic systems to assist the treatment of physical impairments caused due to various conditions like sports injury, spinal cord injury, stroke and other neurological disorders are widely being researched. Since the focus of this PhD is robotics for rehabilitation of physical impairments, further discussions will follow in the next section.

Figure 2.6: Kaspar (Kinesics and Synchronisation in Personal Assistant Robotics)
Image courtesy Dr. Ben Robins

2.5 Robotics for neuro-rehabilitation

Physical impairments due to various neurological conditions could hamper the independent living and effect the social interaction and activities of a person. This would not only result in reduced quality of life but also impact the healthcare costs. Rehabilitation helps in restoring the lost motor functions and application of robotic devices to offer rehabilitation treatments have been widely researched. Several rehabilitation robotic systems offering lower/upper limb rehabilitation are designed and many are continuously being improved based on the clinical evaluations.

Rehabilitation of gait receives utmost focus in sub-acute stages of neurological insults like stroke or spinal cord injury as gait plays a main role in the independent living of the patient (Belda-Lois et al., 2011; Olney et al., 1996). Conventional gait training techniques often require more than one therapist to work with a single patient and are very laborious. Robotic systems offering gait rehabilitation therefore aim to automate the process and decrease the patient to therapist ratio to one to one. Robotic gait rehabilitation systems are are also actively being researched and some product outcomes are already available commercially. The GENTLE/A system is an upper-limb rehabilitation robotic system, hence robotic devices for upper extremities are discussed in further detail in the following sections.

Upper-limb rehabilitation

Regaining the mobility is focussed mainly in the rehabilitation programmes often starting during the sub-acute stage of recovery after a neurological condition such as stroke. The upper-extremities are neglected in the sub-acute stage when there is a good scope for recovery. In order to address this lack of focus on upper-extremity training several upper-limb rehabilitation robotic systems emerged. The human upper-limb activities have a wide range of motion thus it is conceivable that a robot with a good range of motion similar to humans would provide a better service. This could be achieved by various design mechanisms. Though the ultimate aim of all these design mechanisms is to train the upper-extremities, there is a substantial difference in their construction and training strategy. Based on these criteria the current upper-limb rehabilitation devices can be broadly classified as follows:

I. Arm support devices

II. Exoskeletons

III. End-point manipulators

I. Arm support devices

Supporting the weight of the arm assists the patient in making more controlled and meaningful movements in the earlier stages of rehabilitation. This is the basic principle underlying the design of arm support devices. These devices usually utilise cable suspensions from a high mount point. The design mechanics are simple, arm weight is compensated against gravity. The control over the joints is very limited and the devices could offer an average range of motion to the user.

Swedish Help Arm:
Swedish Help Arm (Figure 2.7a) (ElderStore.com, 2013; Stienen, 2009; Reinkensmeyer, 2009) is a counterbalance sling suspension system that can be used both as an assistive or a rehabilitative device. The cable suspensions and the overhead frame support can be adjusted to offer proximal/distal arm support and to suit various patient anatomies. The device can assist in daily living tasks like eating, personal grooming, etc. When used as an exercising device, the counterbalance weights could be adjusted to offer assistance or resistance to the arm muscles.

Freebal:
Freebal (Figure 2.7b) (Stienen et al., 2007b; Stienen, 2009) is a weight support device for upper-limb and the amount of compensation against the gravitational pull could be freely adjusted. The device has a simple design with two cable suspensions easing its transportation and maintenance. The weight support is offered at both wrist and elbow unlike other cable suspensions devices which offer support only at wrist. This double support avoids a

dangling elbow that might strain the shoulder at the same time allows the therapist a full access to the limb while training the patient. The study with patients showed an extended range of motion in the upper-limb with the arm support using Freebal.

NeReBot:

NeReBot (Figure 2.7c) (Rosati et al., 2007; Masiero et al., 2007; Masiero et al., 2011) is a wire-based upper-limb rehabilitation robotic system designed as a low-cost mechanical structure. The system includes a splint for the patient's forearm, a frame with wire suspensions at the top (support the weight of the arm) and base (easy transportation). According to the designers, the NeReBot with it's simple structure (unlike industrial-robot looking systems) has greater chances of acceptability by the patients. The greater transportability allows NeReBot to offer rehabilitation training right from the bedside in sub-acute stages. The clinical trial results of NeReBot with stroke patients showed greater reduction in motor impairments and improved functional abilities when compared to conventional therapy.

II. Exoskeletons

Exoskeletons are external skeletons placed over the arm. It is common to use exoskeletons in robotic gait rehabilitation systems as they offer more control over the joints of the limb. Exoskeletons for upper-limb rehabilitation were designed with the aim to offer rehabilitation training to the upper arm, the forearm and the hand unlike most end-point manipulators which need separate attachments to train different parts of the upper-limb. The powered actuators at both upper-arm and fore-arm joints equip the exoskeletons with greater control and larger range of motion but at the cost of complex mechanics. Described below are some popular exoskeletons and their brief mechanics.

Dampace:

(a) SwedishHelpArm
Image courtesy AliMed, Inc.

(b) Freebal
Image courtesy Dr. Arno Stienen

(c) NeReBot
Image courtesy Prof. Giulio Rosati

Figure 2.7: Arm support devices

Dampace (Figure 2.8a) (Stienen et al., 2007a; Stienen et al., 2009; Stienen, 2009) is an exoskeleton device that could deliver impairment specific force-coordination training and the exercises are framed to resemble the activities of daily living. The primary requirement for exoskeleton devices is to closely match the anatomical axes of the arm with that of the exoskeleton, any mismatch could lead to discomfort and pain while training with the device. The design of Dampace follows the technique of decoupling the joint rotations from the joint translations in order to achieve a close match of robot axes and anatomical axes. The design evaluation shows that the decoupling technique not only reduces the set-up times but also minimizes the interaction forces improving the usability of Dampace as a therapeutic tool.

ArmeoSpring:

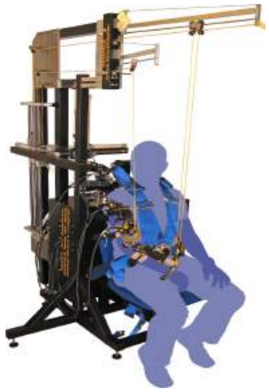
ArmeoSpring (Figure 2.8b) (Gijbels et al., 2011; Colomer et al., 2012; Hocoma.de, 2013) is a commercially available exoskeleton system with 5 DOF (3 in the shoulder, 1 in the elbow and 1 in the forearm). The integrated spring and adjustable arm mechanism in ArmeoSpring allow variable levels of gravity support to the upper-arm. The device can deliver whole arm training with game-like functional exercises through virtual reality environment. Patients with both moderate and severe impairments in the upper-limbs can train independently and clinical evaluation showed patients in favour of therapy with ArmeoSpring compared to conventional therapy.

ARMin:

ARMin (Figure 2.8c) (Nef et al., 2006; Nef et al., 2007) is a semi-exoskeleton device that can enable elbow flexion/extension and shoulder movements. ARMin can deliver a patient-cooperative arm therapy using the position, force and torque sensors. The device includes a haptic display and a audiovisual display that the designers claim would help in increasing the patient's motivation and thereby the therapeutic progress. ARMin allows various therapy modes to suit movement training, game therapy and activities of daily living exercises. The patient-cooperative control strategy follows 'assist as needed' principle that proved to be a good method to maximise patient's participation and motivation during the clinical studies. Later version of ARMin with enhanced features were also designed and are currently under evaluation.

III. End-point manipulators

End-point manipulators are also called end-effector based robots. The patient's hand or forearm is connected to the end-point that controls the movements of the arm. From the construction point of view end-point manipulator robotic systems are easy to realise with simple mechanics. As the end-effector is the only point of contact, the control over the joint rotations is incomplete and range of motion is also limited when compared to ex-



(a) Dampace
Image courtesy Dr. Arno Stienen

(b) ArmeoSpring
Image courtesy Hocoma: Switzerland

(c) ARMin
Image courtesy Dr. Verena Klamroth

Figure 2.8: Exoskeleton devices

oskeletons. Ease of construction made end-point manipulators very popular upper-limb rehabilitation devices and many research groups work with these devices. Few popular end-point manipulator devices, their training strategies and clinical outcomes are presented in this section.

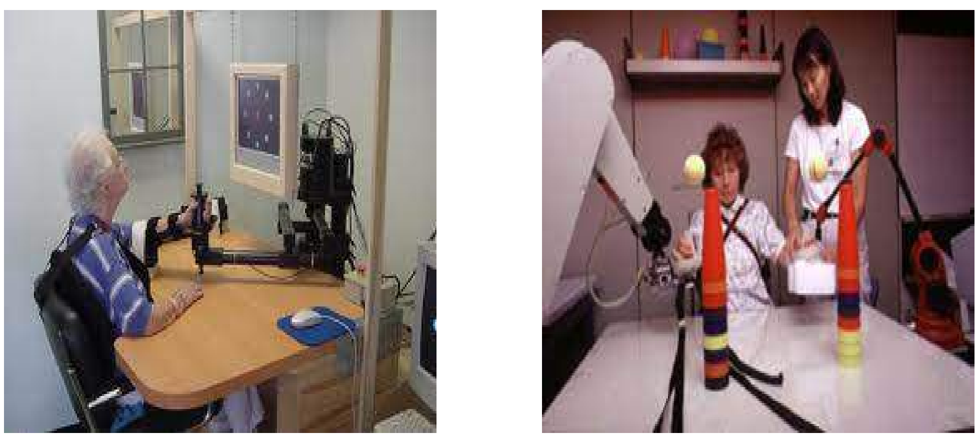
MIT-MANUS:

MIT-MANUS (Figure 2.9a) (Aisen et al., 1997; Krebs et al., 1998) is one of the pioneer robots in the upper limb neurorehabilitation. The planar MIT-MANUS is a 2 DOF robotic device that can assist the movement of patient's arm in horizontal plane and can record details like position, velocity and forces applied. The robotic therapy during the first clinical trials with MIT-MANUS consisted of a set of 'Video games' like drawing circles, stars, squares and navigating through windows. If the patient could not perform the task according to the game's goal, the robot guided the patient's arm to the target (sensorimotor active-assistive mode). The games were designed to evaluate the stroke patient's recovery of upper limb motor function. Both the first clinical trial (Aisen et al., 1997) conducted with MIT-MANUS and the follow up study after 3 years (Volpe et al., 1999) demonstrated significant decrease in motor impairment scores of the effected limb. These results prompted further research into this area leading to the development of new devices to deliver therapy. Further clinical trials (Fasoli et al., 2004) to study the effect of robotic therapy on chronic motor impairments involved a new mode (progressive-resistive mode) of operation of MIT-MANUS along with the sensorimotor mode. In this new mode the patient's performed the same tasks, with the robot generating an opposing force against their movement. The magnitude of this force is controlled by an algorithm based on robotic measures of patient's muscle strength. The results from this trial supported continued improvement in motor function in chronic stroke subjects.

MIME:

Sustaining the motivation of a subject throughout the rehabilitation program is a challenging job and one way to achieve this is to engage the subject in patient controlled exercise (Johnson et al., 1999). MIME (Mirror Image Motion Enabler) (Figure 2.9b) (Lum et al., 1999; Shor et al., 2001) uses this principle to implement bimanual exercises that allow the unaffected limb to guide the therapy of the paretic limb and thereby makes the person initiate and control the therapy in a natural way. MIME comprises a 6 DOF (Puma 560) robotic arm and a 6 DOF digitiser designed for shoulder and elbow neuro-rehabilitation in three dimensional space. The forces and torques between the robot and the affected limb were measured by a 6-axis sensor. The robot can operate in 4 modes, 'passive' where the subject relaxed as the robot moved the limb toward a target with a predetermined trajectory, 'active-assisted mode' where the subject triggered initiation of the movement with volitional force toward the target and "worked with the robot" as it moved the limb, 'active-constrained' mode where the robot provided a viscous resistance in the direction of the desired movement, 'bilateral mode' where the subject attempted bilateral mirror-image movements while the robot assisted the affected limb by continuously moving the affected forearm to the contra-lateral forearm's mirror-image position and orientation. During bilateral mode, the two forearms were kept in mirror-symmetry by a position digitizer, which measured the movement of the unimpaired forearm and provided coordinates for the robot motion controller.

The clinical results from various studies conducted with MIME during chronic (Lum et al., 2002; Lum et al., 2005), and sub-acute (Lum et al., 2005; Lum et al., 2006b) phases show that robot-assisted movements had advantages over conventional treatment of equal intensity in terms of decreasing impairment, improving strength and increasing reach extent, but the two groups were no different at 6-months follow-up. While the MIT-MANUS group focussed on comparing robot-aided therapy with conventional therapy, the MIME group attempted to identify which therapy (robotic/other conventional) can best treat an impairment.



(a) MIT-MANUS
Image courtesy Dr Hermano Igo Krebs

(b) MIME
Image courtesy Dr Peter Lum

Figure 2.9: End-point manipulator robotic systems - I

ARM Guide:

ARM Guide (Figure 2.10a) (Reinkensmeyer et al., 2000; Biorobotics.com, 2013) was designed with the main objective to serve as diagnostic as well as therapeutic tool. It is a 4-DOF robotic device that can assist/resist the linear reaching movement of a patient's arm along a desired track. The device is statically counterbalanced so that it does not gravitationally load the arm. During the initial clinical trials ARM Guide was used as a 'diagnostic tool' to assess various parameters that influence the arm movement in chronic brain injury and as 'therapeutic tool' to provide active-assist training. The results from this study (Kahn et al., 2001) and a later study concluded that robotic assistance has the same effect as the repetitive reaching movement during conventional therapy. Kahn et al., 2006 compared the results from ARM Guide study (used as a therapeutic device) with that of MIME study and concluded that the patients who received movement training with MIME improved their reach extent, but there was no noticeable improvement in the patients who received conventional/ARM Guide training. The authors also reported the design and implementation of enhanced modalities on ARM Guide as future research.

Bi-Manu-Track:

Inspired by the bilateral approach of MIME, Bi-Manu-Track (Figure 2.10b) (Rehab-Stim.com, 2013) was designed to enable bimanual mirror-like exercise of a 1-DOF elbow-movement of the forearm, as well as the wrist. Bi-Manu-Track (Hesse et al., 2003) trains more distal movements as they are considered as integral part of many ADL (other whole-arm training devices are described later in this section). The patients sat at a table with their elbows bent 90° and their forearms put into an arm trough. To switch movement direction, the device was tilted 90° downward and the handles position changed. Three computer-controlled modes were offered: (1) passivepassive, with both arms being moved by the machine; (2) activepassive, with the non-affected arm driving the affected arm; and (3) activeactive, with both arms actively moving against resistance. Results from Hesse et al. (2003) show Bi-Manu-Track can serve as a complementary tool for spasticity management in severe stroke survivors, though the results are not as superior as those from MIT-MANUS and MIME. Result comparison of Bi-Manu-Track training vs electromyography-initiated electrical stimulation (ES) training can be found in Hesse et al. (2005).

ACT^{3D}:

Arm Coordination Training 3D device (Sukal et al., 2006; Ellis et al., 2007; Ellis et al., 2009) was designed to offer impairment-specific training for chronic stroke patients. The system comprises of HapticMaster robot, an experimental chair and a monitor to offer visual feedback to the users. The effects of gravity on the abnormal muscle synergies that result in limited range of motion in stroke sufferers were targeted using the ACT^{3D} system. An intervention that could quantify movement impairments like abnormal joint torque coupling at varying levels of arm-weight support was implemented on the system. The clinical test results (Ellis et al., 2007) showed improved reaching range of motion in chronic stroke subjects.

(a) ARMGuide
Image courtesy Dr. Lennie Kahn and Dr. David Reinkensmeyer

(b) Bi-Manu-Track
Image courtesy Dr. Stefan Hesse

Figure 2.10: End-point manipulator robotic systems - II

2.6 GENTLE/S rehabilitation system

The GENTLE/S is an end-point manipulator robotic system for upper-limb rehabilitation. The GENTLE/S system is the predecessor of the GENTLE/A system, and hence its design, working, clinical outcomes and future scope are discussed in detail in this section.

2.6.1 Design

The GENTLE/S rehabilitation system (Figure 2.11) (Harwin et al., 2001; Amirabdollahian, 2003) was an outcome of a project under the quality of life initiative of framework 5 of the European Commission to evaluate robot-mediated therapy in stroke rehabilitation. It used haptic and virtual reality technologies to deliver challenging and motivating therapy to patients with upper-limb impairments. The GENTLE/S system consisted of

(i) *HapticMaster:* HapticMaster (Linde et al., 2003) is a commercially available robot manufactured by Fokker Control System (now MOOG BV) that can offer an effective haptic sensation. The robotic arm of the HapticMaster has three active degrees of freedom. The end-effector benefits from force sensors that are utilised in admittance control of the device. The device records 3D Cartesian positions, velocities and forces.

(ii) *Frame:* The GENTLE/S system consisted of a frame to support overhead spring suspensions, two sliding chairs for the patients to be seated and a rotatable arm with a display monitor. The frame was designed to facilitate training for both right or left hemiplegic patients.

(iii) *Shoulder support mechanism:* An orthosis with two connected cuffs (one for upper arm and other for forearm) was used for shoulder support. The orthosis was hooked to spring suspensions on the overhead frame. These adjustable constant force springs compensated the weight of the arm.

(iv) *Wrist support mechanism:* A ring gimbal that was attached to the end-effector of the HapticMaster and a wrist cuff formed the wrist support mechanism. The wrist cuff was connected to the ring gimbal using a magnetic linkage that could quickly be released when needed. Wrist support mechanism was designed primarily for patients without the grasp ability.

(v) *Virtual Reality environment:* The virtual reality environment was developed to create a game-like exercise. This technique is followed by many research groups to interest and motivate the patient in taking part in the training. The virtual reality in the GENTLE/S was created with varying complexities to suit patients with varying abilities. A simple interface representing the haptic workspace with least graphic detail was developed to provide awareness of physical space and movement for patients in sub-acute and acute stages. A slightly complex environment that replicates the details of the training environment and a more complex three dimensional graphical environment for providing more motivational and challenging game-like exercises were developed, described in detail in Loureiro et al., 2004; Loureiro et al., 2001

2.6.2 Training methodology

The ultimate goal of rehabilitation is to (re)train the lost motor skills. As the natural human arm movements are smooth, the target for robot-assisted movement training is to achieve a smooth transition pattern. Mathematical models to achieve the smoothness and coordination of human arm movements were developed. Research (Wolpert et al., 1995; Flash et al., 1985) shows that models that mimic the movement by predicting the next state (in terms of position or velocity) based on the current state and motor command are more favourable. Minimum jerk theory is one such theory that mimics human arm movement. Jerk is the rate of change of acceleration or a third time derivative of the position. Minimising the jerk provides a smooth movement trajectory. A polynomial that would minimise the jerk and offer smooth transition given the starting and the ending points in a 3D workspace was derived. The HapticMaster was programmed to follow the Minimum Jerk Trajectory (MJT) (Amirabdollahian et al., 2002) to offer smooth transition during point-to-point movements within the workspace of the robot. Using the MJT polynomials three modes were implemented on the GENTLE/S system and the name of each mode indicated the role of the patient during the mode. These modes were designed as copies of clinical interventions followed during various stages of post-stroke recovery.

1. *Passive:* The user is 'passive' and the robot executes the entire movement according to the MJT within pre-set time. This mode is developed for patients who lack sufficient strength to move.

2. *Active-assisted:* The user has to initiate the movement and the robot assists the movement through the reference path (MJT) with-in the set duration. This mode is suitable for more able patients who can initiate the activity and in this mode the robot and the patient work in co-operation.

3. *Active:* The user is 'active' and executes the entire activity. This mode is more suited for later stages of post-stroke recovery when the recovery progresses. The user is allowed unlimited amount of time to finish the task on their own. The robot follows the user's path and provides haptic assistance to correct the error when the user deviates from the reference trajectory.

Further details about the modes and their operation could be found in (Loureiro et al., 2003).

2.6.3 Clinical results and future scope

The clinical trials with GENTLE/S (Coote et al., 2008; Amirabdollahian et al., 2007; Amirabdollahian, 2003) were conducted at two centres: the Battle Hospital, Reading, United Kingdom, and the Adelaide & Meath Hospital, Dublin, Republic of Ireland. The most striking finding of these trials was that no two subjects had the same response to the intervention. This throws a challenge to the robotic therapy to provide a tailored training according to the patient's needs and 'response' during the therapy.

The analysis of the results from these two trials also suggests future research to investigate the effects of more challenging, motivating, interactive (involving decision-making like in real life situations) contexts during therapies.

Figure 2.11: GENTLE/S rehabilitation system
Image courtesy Prof. William Harwin

Whole-arm rehabilitation devices

The initial versions of end-point manipulator robotic systems focussed on upper arm and forearm rehabilitation, as this is easy to realise with a single point of control. Many of the activities of daily living need fine motor skills of the hand like grasping. Lum et al., 2006b emphasised the need for additional research to develop devices that integrate wrist and finger function along with the upper and forearms. This led to the development of attachments for the end-point manipulators that would train the hand. Couple of works are presented here as examples.

MIT-MANUS

The work on planar MIT-MANUS (shoulder-elbow therapy) has extended to the anti-gravity module (Krebs et al., 2004) (spatial training for the shoulder-and-elbow involving vertical arm movements), and the wrist robot (Rijnveld et al., 2007) (3 active degrees-of-freedom: abduction-adduction, flexion-extension, pronation-supination) and lastly hand robot (Masia et al., 2007) offering whole-arm upper-extremity rehabilitation.

Gentle/G

The Gentle/G rehabilitation system (Figure 2.12) (Loureiro et al., 2007) was designed with a grasp assist unit that can work in co-ordination with the hardware and software of the GENTLE/S system. The grasp assist unit can treat more distal joints (like wrist joint) of the upper limb and when used with the GENTLE/S system it can offer a total of 9 DOF. The software design of the Gentle/G also addresses the synchronisation of HapticMaster and grasp robot and simulates highly interactive and motivating virtual worlds. The Gentle/G system includes a new 4th mode (patient free mode, where the robot follows the patient) for the HapticMaster robot and three grasp modes. The preliminary results from the clinical trials with Gentle/G system are reported in Loureiro et al., 2009.

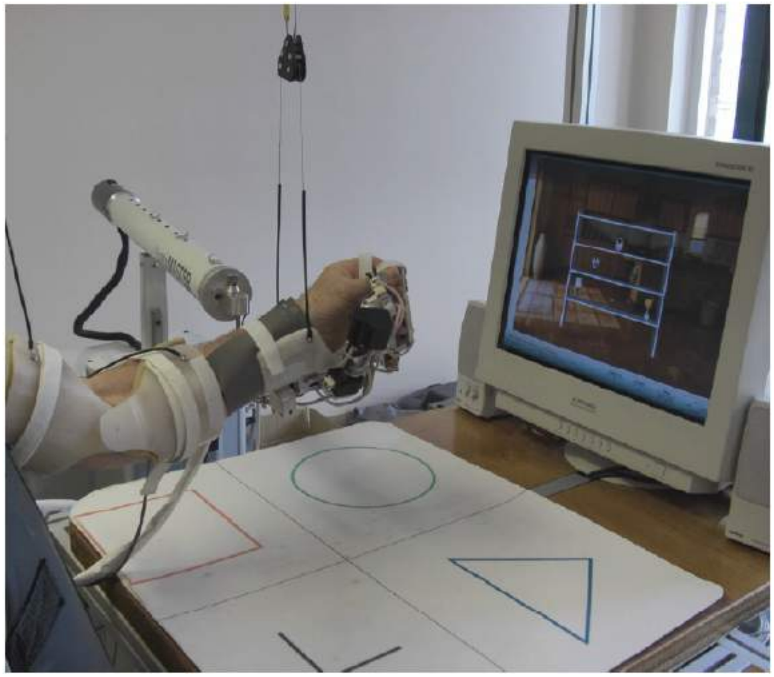


Figure 2.12: GENTLE/G rehabilitation system with Grasp Assistance robot module
Image courtesy Dr. Rui Loureiro

2.7 Reviews of upper-limb robotic rehabilitation devices

With the increasing ageing population in many countries and predicted increase in neurological illnesses such as stroke, the need for rehabilitation is ever growing. In order to address the increasing rehabilitation needs and ease the pressure on therapists many rehabilitation robotic systems have emerged. These systems are under continuous evaluation and their design mechanisms are constantly enhanced based on the evaluation results. In order to guide the design of upper-limb rehabilitation devices, different research groups have attempted to evaluate the outcomes from various robot-assisted rehabilitation studies and presented the future direction and scope of rehabilitation robotic devices in their reviews. The aim, inclusion criteria of the studies, the conclusions and the future direction from four such reviews are presented below (as reported by the authors in the articles):

Prange et al., 2006

Aim: To investigate the effect of robot-aided therapy on the upper-limb motor control and functional abilities of stroke patients.
Inclusion criteria: Clinical trials with a robotic device to train upper-limb impaired stroke patients. The outcome measures of the clinical trials must be reported in a peer reviewed journal.
Conclusion: The robot-aided therapy is a promising new approach to rehabilitation of upper-limb motor control after stroke. It improves short-term and long-term motor control of the paretic shoulder and elbow in sub-acute and chronic patients; however, we found no consistent influence on functional abilities.
Future direction: Future studies must evaluate the appropriateness of various modalities of the robot-aided training for different patient groups. The effectiveness of robot-aided therapy when compared to other approaches of stroke rehabilitation such as pharmacology or constraint induced movement therapy must be investigated.

Kwakkel et al., 2008

Aim: The aim of the study was to present a systematic review of studies that investigate the effects of robot-assisted therapy on motor and functional recovery in patients with stroke.
Inclusion criteria: Randomised Control Trials (RCTs) with upper-limb impaired stroke patients in which the effect of robot-aided therapy was investigated and the outcome was measured in terms of motor/functional recovery of the upper-limb.
Conclusion: No overall effect in favour of robot-assisted therapy was found and no significant improvement in ADL was found; however studies showed significant improvement in upper-limb motor function with robotic training.
Future direction: Future research on the effects of robot-assisted therapy should focus on

kinematic analysis to differentiate between recovery by neural repair and recovery based on compensation strategies. Robotics has the potential to offer stroke patients an opportunity to train independently in an intensive functional fashion and at home.

Mehrholz et al., 2009

Aim: To evaluate the effect of electromechanical and robot-assisted arm training for improving arm function in terms of impairments and activities of daily living of patients after stroke.

Inclusion criteria: Randomised controlled trials comparing electromechanical and robot-assisted arm training for recovery of arm function with other rehabilitation interventions or no treatment for patients after stroke and outcome measures reported in terms of ADL.

Conclusion: No evidence that the use of electromechanical-assistive devices in rehabilitation settings may improve activities of daily living was found. However, we found evidence that arm function and strength may improve. As adverse events and drop outs were very rare in the studies analysed, the reviewers opine that the use of electromechanical and robot-assisted arm training devices might be safe and acceptable to most participants.

Future direction: Well designed, multi-centred large-scale studies are needed to evaluate the effectiveness of the robot-assisted training and future analysis should focus on outcome measures in ADL.

Rosati, 2010

Aim: To briefly outline the strengths and shortcomings of robotics in post-stroke rehabilitation and to help the reader gain an insight on the present and prospective role that robotics may play as a complementary tool to current movement training programs.

Inclusion criteria: This article is an expert review by author with a good experience in the area of rehabilitation robotics. The author's work in the area led to the development of several prototype robotic systems for post-stroke upper-limb rehabilitation, one of them being the NeReBot (presented earlier in this chapter under 'Arm support devices').

Conclusion: Robot-assisted training in addition and/or partial substitution of conventional therapy, so far was demonstrated to be more effective when compared to conventional therapy only. However the benefits provided in terms of functional outcome are very small.

Future direction: Future research should focus on identifying how the robotic training can enhance ADL, whether through technical design and/or new treatment exercises and protocols. The scope of robotic technology in different domains of rehabilitation, such as in the large family of neuro-degenerative diseases, need to be further explored

The large-scale multi-centred study conducted by Lo et al., 2010 attempted to address the areas highlighted by these review reports. The study concluded that "In patients with long-term upper-limb deficits after stroke, robot-assisted therapy did not significantly improve motor function at 12 weeks, as compared with usual care or intensive therapy. In secondary analyses, robot-assisted therapy improved outcomes over 36 weeks as compared with usual care but not with intensive therapy".

All the reviews reported in this section concluded that no significant improvements in ADL function could be found with robot-aided therapy; however motor strength and motor function of the paretic arm can improve with robotic assistance during therapy. They also conclude that robotic therapy will have largest impact if patients can be motivated to train independently in an intensive functional fashion.

2.8 Research Questions

This section describes the development of research questions (re-presented below) in the wake of literature review presented in this chapter.

RQ1: Can the contribution of the user/robot be identified during a HRI session with the

GENTLE/A rehabilitation system?

RQ2: Can this identification of contribution be further utilised as a performance indicator?

RQ3: How can the performance indicators be used to improve the adaptability of the GENTLE/A rehabilitation system?

The findings from the review reports were also supported by the studies showing that with appropriate technology, the role of the therapist during highly repetitive movement training protocols such as constraint-induced (CI) therapy (Dickstein et al., 1986; Lum et al., 2004; Lum et al., 2006a) can be reduced without loss of treatment effectiveness. This brings out the need for robotic therapy to be highly 'adaptable' according to the specific needs and performance of the patient, if the patient has to train independently (addressed by RQ2 and RQ3).

Research (Kahn et al., 2006; Rosati, 2010) also highlights the capability of robotic devices to capture many kinematic and dynamic parameters of movement. This rich stream of data could be an indicator of patient performance and could also enhance the usability of robotic systems as effective assessment tools. The GENTLE/S literature also conveys that the assessment capability of the system was not explored and clinically tested (addressed by RQ1 and RQ2).

2.9 Adaptability strategies

It is popular to use various modalities to suit patients in various stages of post-stroke recovery by the robotic rehabilitation system. Research groups have followed various strategies to design these modalities. The underlying principle is to offer assistance in early stages of post-stroke recovery and gradually reduce the assistance (or transform into resistance) as the recovery progresses. These strategies are also often referred in the literature as performance-based progressive training schemes. MIT-MANUS (Krebs et al., 2003) uses the mean velocity and the deviation from the reference trajectory to alter the amount of guidance offered to the patient. Similarly ARM Guide (Reinkensmeyer et al., 2000) drives the patient's arm along a reference trajectory allowing a deadband (of small width) of error around the desired path. A position feedback controller was used by ARM Guide to assist the arm to reach the target. Similar such control algorithms were developed and implemented in other upper-limb rehabilitative devices.

A rehabilitative training is thought to be successful if it can motivate the patient to train more in the early stages and make the task progressively challenging as the recovery progresses. Research groups developed algorithms to alter the amount of guidance offered to accomplish a task based on the performance of the patient. If the patient needs to be motivated in the initial training stages, we believe that the rehabilitative system has to auto-tune the task at hand to suit the current performance of the user. The progressive training schemes that do not auto-adapt, require correct identification of patient status and then tuning by the therapist, which leaves this as a subjective task and open to variability. This is while auto-tuning based on quantitative performance measures can simplify this paradigm while offering some degree of standardisation across different robotic systems used. Therefore during our research, we attempted to enhance the adaptability of the GENTLE/A system by developing algorithms that would auto-tune the task to the user's ability and later progress to make the task challenging.

Similar approach was investigated by another research group (Colombo et al., 2012; Panaresse et al., 2012; Casadio et al., 2009). The Progressive Task Regulation (PTR) (Colombo et al., 2011) algorithm proposed by this research group evaluated the performance of the patient and automatically changes the features of the task according to the patient's ability. The algorithm was implemented on a planar end-point manipulator robot (Braccio di Ferro (Casadio et al., 2006)) with 2-DOF. The features of the task such as the sequence of point-to-point movements, the type of assistance from the robot and target distance were altered by the PTR according to the patient's ability. The default difficulty level of the task is set based on the performance of the patient in an initial evaluation session. The PTR then alters the task parameters based on the patient's ability after every training session. The algorithm was tested on both simulation data and performance data obtained from 9 stroke patients where a physiotherapist manually altered the difficulty level of the task. The results showed that the behaviour of PTR algorithm is quite similar to the manual changes made by the therapists. Detailed results could be found in Colombo et al., 2011.

The adaptive algorithms developed during this research follow a similar approach as the PTR, but the parameters altered to achieve the task regulation are very different. PTR evaluates the performance of the user at the end of a training session and alters the features of the task on a session by session basis. While our algorithms follow different set-points for performance evaluation and alter the task features at regular intervals within an experimental session. The interval between consecutive performance evaluations was adapted from the Rehabilitation Gaming System (RGS) (Cameirão et al., 2010). RGS implements an individualised training approach that is adjusted according to the user's capabilities and was successfully evaluated with stroke patients.

Furthermore, the adaptive algorithms developed during this PhD were implemented on HapticMaster with a three dimensional workspace (as opposed to planar workspace with Braccio di Ferro). The algorithms were evaluated dynamically on the live data while healthy users were taking part in the experimental sessions. The adaptive algorithms and the experiments that evaluated the algorithms were described in detail in the later chapters of this thesis and show promising results.

2.10 Discussion

The advancements in the development of robotic devices for rehabilitation purposes could be mainly connected to the rapidly growing rehabilitation needs. Robotic training devices are being viewed as advanced tools to physically assist the therapist and also reduce therapist monitoring time. Successful application of robotics in contemporary fields like assistive technology is also promoting the research in area of rehabilitation robotics. Apart from serving as training tools, rehabilitation robotic devices have the potential to offer performance feedback and a scope of tele-rehabilitation at the patient's home.

Rehabilitation robotic devices for upper-limb training being the focus of this PhD, various design types and popular devices under each type were presented in section 2.5. Though the ultimate aim of these devices was to train the upper extremity, various training strategies were followed, clinically tested and the devices are being constantly improved based on the results.

In order to investigate the impact of several upper extremity training devices and define the future direction, reviews were conducted by research groups. The major review reports concluded that no significant improvements in ADL functions could be found with robot-aided therapy; however motor strength and motor function of the paretic arm can improve with robotic assistance during therapy. Large scale multi-centre clinical studies were recommended by the review reports to clearly establish the impact of the robot-assisted training. The reviews also concluded that robotic therapy will have largest impact if it can facilitate self-manageable training to the patients. Furthermore, the parameter recording capability of the robotic devices that could be an indicator of the patient performance was identified as an unaddressed area of robot-aided rehabilitation.

The robot-assisted rehabilitation could be made self-manageable (at least partly) if the training system can auto-adapt to the performance of the user. So the primary aim of the research during this PhD was to enhance the adaptability of the GENTLE/A rehabilitation system. In order to achieve the adaptability we focussed on using the parameter recording capability of the HapticMaster robot. Hence the initial studies focussed in identifying the contribution of the user/robot during a HRI session using the parameter recording capability of the HM. In the next stage the usefulness of the parameters recorded as performance indicators was evaluated. The subsequent studies evaluated the adaptability strategies proposed to suit various stages of recovery using these performance indicators. The aims of studies conducted, the results and their analysis are presented in the next chapters of this thesis.

2.11 Conclusion

This chapter mainly presented the research background to this thesis. The need for rehabilitation and the role of robotic assistance in rehabilitation was briefly introduced. The contribution of robotics to the medicine and healthcare sectors was discussed and some popular robotic devices were presented. Afterwards, a summary from review reports related to upper-limb robotic rehabilitation devices was presented. The research questions proposed in Chapter 1 were reviewed based on the background research. Finally studies trying to address similar research questions were discussed in further detail and the strategy adapted during this research to address the research questions was elaborated.

Chapter 3

Identifying the performance indicators

The previous chapters presented the stroke statistics, increasing rehabilitation needs and the role of rehabilitation robotic devices in this context. If the rehabilitative training has to be made self-manageable (at least partly), the rehabilitation robotic device should autonomously adapt to the performance of the user and this highlights a need for a performance indicator. This chapter demonstrates the initial investigations carried out during a pilot study and a subsequent main study towards identifying such performance indicators.

3.1 Introduction

The background presented in Chapter 2 draws attention to the recent developments in rehabilitation robotic devices 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 HM's sensors are capable of recording various parameters of the user's movements like the positions, velocities and forces. We aimed to take advantage of this capability of the HM's sensors to identify human contributions during interactions and use this to enhance the adaptability of system. In the process of this investigation we conducted a pilot study (PS-I) followed by a main study (Exp-I) that are presented in this chapter.

This chapter is organised as follows: Section 3.2 presents the key research questions addressed by PS-I and Exp-I and Section 3.3 describes the experimental set-up used for these studies. Section 3.4 describes the aims, experimental protocol and analyses the results from PS-I. Section 3.5 presents details of Exp-I and the following section discusses the results from this study.

3.2 Research Questions

RQ1: Can the contribution of the user/robot be identified during a HRI session with the GENTLE/A rehabilitation system?

The HM was programmed to follow a reference trajectory (Minimum Jerk Trajectory, (MJT)) (Amirabdollahian et al., 2002). HM's end-effector can record position, force and velocity data. We attempted to compare the positional coordinates of the actual trajectory achieved by the user with that of the MJT to understand the role of the user/robot during a HRI session. Therefore the studies presented in this chapter aimed to explore whether it is possible to identify if a robot or a person is leading the interaction by comparing the results from the performance of the user recorded by the system, with the reference model used to guide the movement of the robot's end-effector.

Hypothesis: Our underlying hypothesis while comparing the system recorded data with the MJT was that the system recorded data would reflect the (user+robot)'s performance while the MJT would reflect the robot's performance.

RQ2: Can this identification of contribution be further utilised as a performance indicator?

If comparing the actual performance with the MJT could successfully indicate the role of the user/robot during an interaction, our next aim was to investigate if the comparison can also indicate the contribution by the user/robot during an interaction. Exp-I aimed to partially address *RQ2* in identifying a performance indicator.

3.3 Experimental set-up

The experimental set-up for the GENTLE/A ('A' for adaptive) system used the hardware and the software components of the GENTLE/S rehabilitation system with some modifications. These modifications were solely implemented by the author and provided a platform for the studies presented here.

3.3.1 Hardware modifications

The HapticMaster with its gimbal attachment formed the vital component of the GENTLE/A system. The 24" wide LCD screen for display stands on a rotary arm, which can be turned from one side to the other side of the exercise table and thus can be adjusted based on the dominant side of the participant. Due to the participation of healthy volunteers, the overhead frame support mechanism, elbow orthosis and magnetic wrist attachment of the GENTLE/S system were excluded.

3.3.2 Software modifications

The current setting uses Window 7 (64 bit) and was programmed using Visual Studio 2008, with the C++ programming language. Data during interaction can be captured using comma delimited files. The graphical user interface was developed under OpenGL. A comparison of system specifications of GENTLE/S system vs GENTLE/A system is presented in Table 3.1.

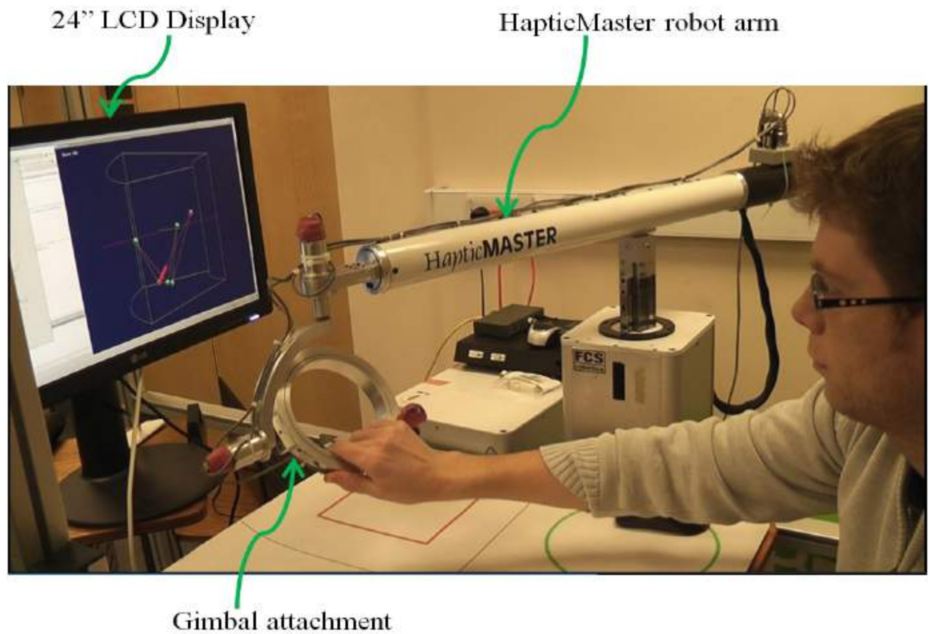


Figure 3.1: Experimental set-up of the GENTLE/A system in PS-I

3.3.3 Modes of operations

The GENTLE/S system operated the HM in three modes (Loureiro et al., 2003) mainly designed to assist the participants in various stages of post-stroke recovery. These three modes of operation were re-programmed for use with the GENTLE/A system:

- Passive Mode: Participant remains passive holding the gimbal attachment to the robot's end-effector while the robot executes the movement from source to target in

Table 3.1: Comparison of System specifications (GENTLE/S vs GENTLE/A)

Specification	Pre-existing GENTLE/S system	Current GENTLE/A system
Platform	Microsoft Windows NT	Windows 7 (64-bit)
Visual Studio version	Visual Studio 6.0	Visual Studio 9.0
Programming language	C++	C++
Data Back-up	Access database	File database (comma separated file)
Graphics	Open Inventor (OI)	OpenGL

its workspace.

- Active-Assisted Mode: Participant has to initiate the activity, and the robot assists whenever the participant fails to progress. Thereby in active-assisted mode, participant and robot work in coordination to reach the target.

- Active Mode: Participant has to execute the entire movement from source to target. The job of the robot in the active mode is to correct the deviations, if any, from the desired path.

The participant could initiate and execute movement between targets in the active-assisted mode while in the passive mode the robot cycled by itself through these defined points. The movement between a source and a target point was termed as a *'segment'* and a duration of 4 seconds was set to execute each segment. All numbered points were visited sequentially. The segment starting at a source point *'k'* and ending at a target point *'k+1'* was referred to as *seg-k*. There was a small delay of 3 seconds between any two consecutive segments. The time given to execute a segment (4s) and the delay (3s) between consecutive segments were obtained from the GENTLE/S data, where the durations were assumed to be suitable in clinical trials.

3.3.4 Virtual Reality environment

Development of a new graphical user interface (GUI) using OpenGL allowed the experimenter to insert the target points that were displayed as numbered spheres in green. The GUI also rendered a pipe (presented as a cylinder graphically) connecting these points (Figure 3.2). This connector pipe acted as a guide to the desired straight-line path between the source and the target points. The end-effector position was displayed as a small yellow ball moving in the workspace of the robot.

When the participant was due to start the movement from the source of a segment, the target point glowed in pink and once the participant reached the target point, it turned green becoming the source for the next segment and the target for the subsequent segment glowed in pink and so on. The progress along the desired MJT path for the segment was displayed as a grey cylinder and the actual path achieved by the participant was displayed as a red cylinder. The angular deviation from the desired path was calculated as θ and when $\theta > 10^{\circ}$, a green arrow was displayed informing the participant of the direction in which the movement was deviating. During the delay between segments the target point for the next segment gradually grew in size and popped (like a balloon), serving as both an audio and a visual cue for the participant to start the movement towards the target. Additional audio cues in the form of human voice in the background to indicate starting and ending of various modes were created using Acapela-group.com, 2013.

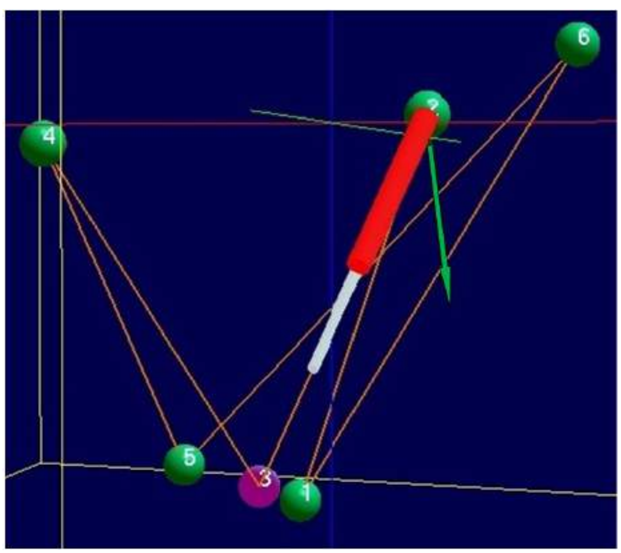


Figure 3.2: VR environment showing the execution of segment-2, target point in pink, progressing grey and red cylinders and deviating green arrow. Points 1, 3 and 5 were located closer to the participant's body and points 2 and 4 were located farther away from the participant's body.

3.4 Exploring usefulness of 'position data' (PS-I)

The pilot study focused on identifying whether a human or the robot is leading during a reaching segment, where the user reaches for an object in the workspace. The first parameter identified and used was the positional lead/lag versus the MJT reference trajectory. We hypothesised that leading or lagging from the reference trajectory is associated with the effort exerted by the user towards achieving the target. This section presents our pilot study and its results to support the hypothesis.

3.4.1 Experiment

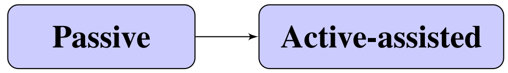
3.4.1.1 Participants

Three healthy participants (2 male and 1 female) took part in the experiment with their age ranges 25 to 32 yrs. Written informed consent was obtained from each participant before inclusion in the studies and ethical approval of the evaluation protocol was obtained from the University's ethics committee (under University of Hertfordshire approval number 1011/16).

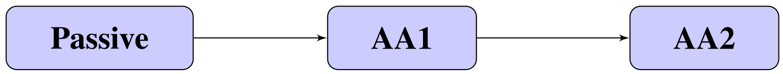
3.4.1.2 Methods

The experimental procedure was designed after considering the common challenges faced in the field of Human-Robot Interaction (HRI) (Goodrich et al., 2007). The experiment was conducted in two phases (see Figure 3.3):

Training Phase: The participant was instructed to hold the ring (gimbal) (see Figure 3.1) attached to the end of the robotic arm and move the ring to match the trajectory shown on the screen. The participant was allowed to understand the operation of the system by moving his/her arm and observing the movement of the small yellow ball (VR representation of the robot's end-effector) on the screen which directly mapped to the



(a) Training (PS-I)



(b) Actual-performance (PS-I)

Figure 3.3: Experimental protocol (PS-I)

movement of robot's end-effector in the 3D space.

Actual Performance Phase: Once the participant was familiar and comfortable with the activity, the actual performance phase was executed. The actual performance phase involved executing the passive mode once followed by two repetitions of the active-assisted mode.

Each mode needed cycling through a set of points by navigating from point 1 to point 2 (thus completing seg-1) and so on. In order to create a situation where the participant purposely led the activity, the active-assisted mode was executed twice. The first repetition was termed Active Assisted-1 (AA1) where the participant was instructed to initiate the movement at the source point and then allow the robot to take charge of the movement until the target point was reached. The second repetition was termed Active Assisted-2 (AA2) and the participant was asked to execute the entire movement from the source to the target points while trying to overtake the robot using the virtual representation of the grey and the red cylinders. During the experiment, Cartesian positions, forces, and velocities were sampled at a time interval of 50 milliseconds.

In order to keep the data analysis simple and avoid varying influence of gravity, this study was restricted to reaching movements (movements away from the participant's body) in single axis and horizontal (XY) plane. To ensure the observations hold for various possible combinations of X and Y positions in the horizontal plane three paths shown in

Figure 3.4 were chosen. Path 1 represents equal contribution from both X-axis and Y-axis positions, path 2 with a more pronounced contribution from Y-axis positions and path 3 with a more pronounced contribution from X-axis positions. Data was recorded for the movements along these three paths (see Figure 3.4).

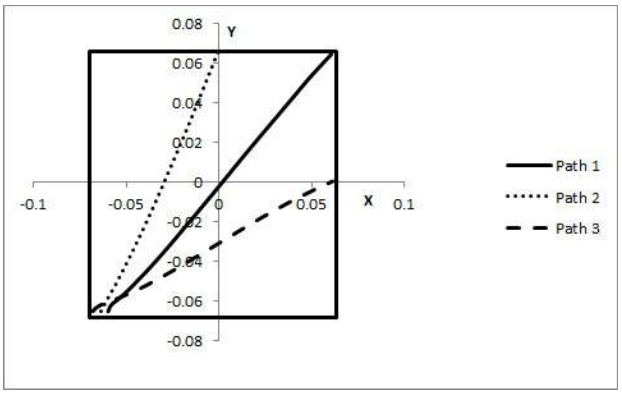


Figure 3.4: Paths followed during horizontal XY plane movements

3.4.1.3 Terminology and parameters

Tau (τ): A parameter, τ, was calculated using the sample time *(t)*, time at the start *(t_{start})* and time at the end *(t_{end})* of each trajectory segment:

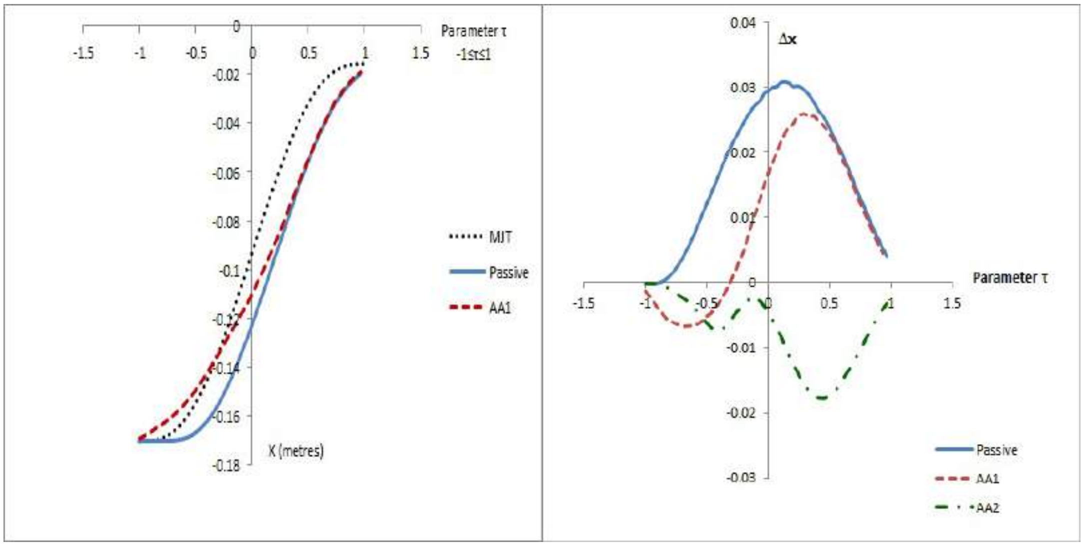
$$\tau = 1 + \left(\frac{2}{t_{end} - t_{start}}\right)(t - t_{end}) \text{ where } -1 \leqslant \tau \leqslant 1$$

This was a parameter of convenience used to map the exercise time to a parameter between -1 and 1, which allows for considering all trajectories using the same temporal window.

3.4.2 Results and Analysis

Data was collected during both training and actual performance phases of the experiment, but only the data from actual performance phase was used in the data analysis.

Figure 3.5a was plotted from the data recorded with Participant 1. The plot shows a comparison between actual-X positions achieved by the participant with that of the desired MJT-X positions that were used to drive the robot arm. The movement was along the Cartesian X-axis.



(a) Tau vs X-axis positions (MJT/Passive/AA1) for Participant 1

(b) Tau vs Δx (Passive/AA1/AA2) for Participant 1

Figure 3.5: Plots for Participant 1

To clearly understand the deviation of the actual trajectories from the reference trajectory, a new parameter Δx was introduced:

$$\Delta x = x_{MJT} - x_{Actual} \tag{3.1}$$

This parameter presented the differences between the reference trajectory position (x_{MJT}) and the actual position recorded by the robot (x_{Actual}) for every sampling interval.

Figure 3.5b shows *Tau (τ) vs* Δx for Participant 1 during the passive, AA1 and AA2 modes. The series obtained for the passive mode shows that Δx was always positive which according to Equation 3.1 indicates that the actual-X positions recorded during the passive mode were always lagging the MJT-X positions. Comparing the series obtained for the

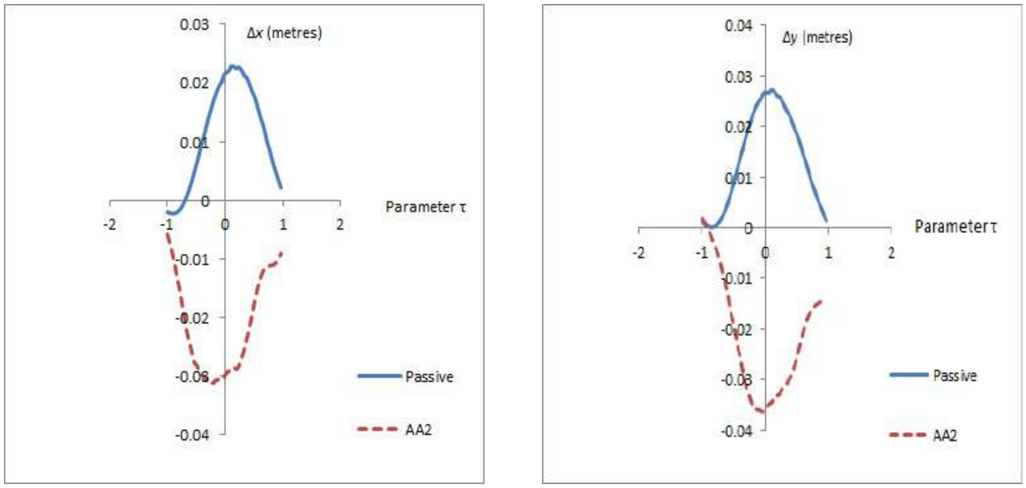
Table 3.2: Leading-Lagging role of the participant/robot during various modes (PS-I)

Mode	Participant's role	Robot's role	Observation
Passive	Lagging	Leading	$\Delta x > 0$
AA1 (Initial force by participant)	Leading	Lagging	$\Delta x < 0$
AA1	Lagging	Leading	$\Delta x > 0$
AA2	Leading	Lagging	$\Delta x < 0$

AA1 mode with that of the passive mode, the AA1 series has an initial dip where Δx was a negative value and then follows the same trend as the passive mode where Δx was a positive value. This correlates with our request to the participants to only contribute to initiation of movement and then allowing the robot to complete the segment by remaining passive. Table 3.2 summarises the observations during the passive and active-assisted modes of operation.

Table 3.2 shows whenever Δx is a positive value, robot was leading the activity and whenever Δx is a negative value, the person was leading the activity. The plots with data recorded during Y-axis movements showed similar pattern as reported in Table 3.2. The next step was to test whether these findings also hold true for the data recorded during horizontal (XY) plane movements. Figure 3.6 shows the Δx and Δy (= $y_{MJT} - y_{Actual}$) plotted against parameter τ for Participant 3 during 'Path 1' in Figure 3.4. The Δx from Figure 3.6a and Δy from Figure 3.6b show a negative value for AA2 mode. This is in agreement with the observations shown in Table 3.2.

As this pilot study formed the basis for our subsequent main experiment where the observations from this study were tested with greater number of participants in varying conditions, two further conditions were examined with the repeat of 'actual performance': Condition-1: Horizontal XY plane at an elevation, a Z-component was introduced to study the effects of gravity on the movement trajectory. The participant was asked to maintain a constant Z-component, no arm support was provided to compensate gravity.



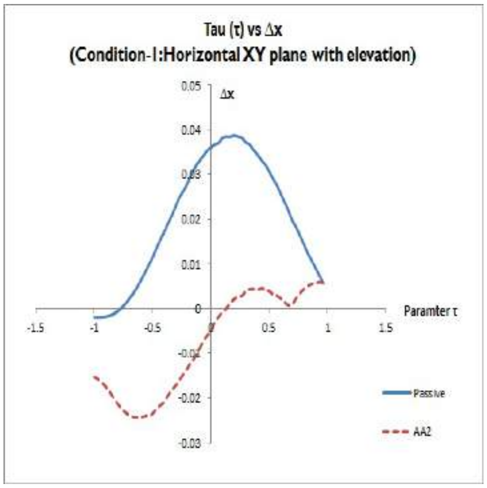
(a) Tau vs Δx for Participant 3 **(b)** Tau vs Δy for Participant 3

Figure 3.6: Plots for Participant 3 during 'Path 1'

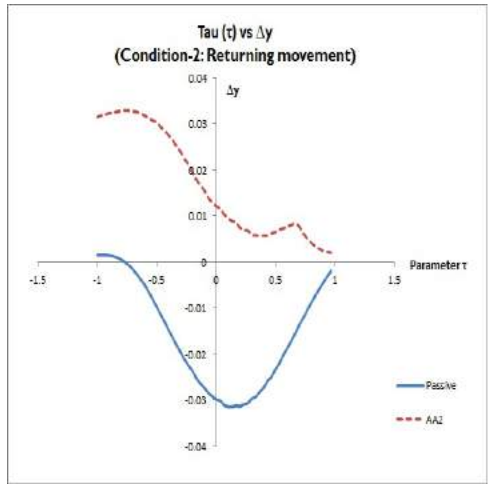
Condition-2: Returning movement, moving from a source located farther away from the body to the target closer to the body of the participant.

Figure 3.7 shows the plots from the data collected during condition-1 and condition-2. The Δy from condition-1 during active-assisted mode is in agreement with the findings from single axis and planar movements without elevation, however, Δx did not remain negative for the entire movement during AA2 mode (see Figure 3.7a). This informed that our hypothesis, in its current form, might not be sufficient to identify the lead-lag role of the participant under varying influence of gravity.

During condition-2 as the movement was a returning towards the body movement, where the values of both the positional coordinates (x, y) decreased as the movement progressed from source to target, it affected the sign for the Δx and Δy. Our observation (see Figure 3.7b) showed that Δy was negative during passive mode and was positive during AA2 mode which is exactly opposite to our previous findings (e.g., Figure 3.6). This revealed that our hypothesis will also be influenced by the direction of the movement (away or towards point of origin) and would need to further account for these sign variations by



(a) Tau vs Δx (Condition-1) for Participant 3



(b) Tau vs Δy (Condition-2) for Participant 3

Figure 3.7: Plots with Condition-1 and Condition-2

incorporating the direction of the movement into lead-lag interpretation.

3.4.3 Intermediate findings

The PS-I data analysis used the position data recorded to identify the role of the user/robot during a HRI session. The results obtained show that it is possible to identify whether the HapticMaster robot, or the participant were leading the interaction modelled by the MJT on a single-axis or planar point-to-point movements without elevation. The analysis also showed that negative error can be used as an indication for the robot’s lead and positive error can be used as an indication for the participant leading the point-to-point moving task. However, the results from the data collected with two new conditions informed that our approach required further improvements.

3.5 Transition to 'vector space' (Exp-I)

It can be inferred from the results of PS-I that the coordinates of position being scalars, the direction of movement affected the sign of $\Delta x/\Delta y$. Hence the plots could not always elaborate on the lead-lag role of the participant, using same interpretations, i.e., using the positive or negative sign. This prompted a move to vector space where movement direction was captured by the direction in which vector was heading. Hence projection and deviation of the movement vector have a better chance to inform the lead-lag role of the participant without being influenced by the direction of movement. In order to test this new approach in a 3-dimensional workspace and also with greater number of participants, we designed and conducted a study (Exp-I) that is presented in this section.

3.5.1 Experiment

3.5.1.1 Participants

Twenty healthy volunteers (15 male and 5 female) took part in the study aged between 23 and 60 years (mean 36.9 $\pm$ 11.3 standard deviation). Exp-I was conducted with the same ethical approval protocol number (1011/16) as PS-I obtained from University of Hertfordshire's Ethics committee.

3.5.1.2 Terminology and parameters

Two new parameters, 'Effort' and 'Error', were computed to aid vector space analysis (Figure 3.8).

$$Effort_{Actual} = \overrightarrow{AC}\cos\theta$$

$$Error_{Actual} = \overrightarrow{AC}\sin\theta$$

$$\theta = \arccos\left(\frac{\overrightarrow{AB}.\overrightarrow{AC}}{|\overrightarrow{AB}||\overrightarrow{AC}|}\right)$$

where $(\overrightarrow{AB}.\overrightarrow{AC})$ is the dot product of the vectors

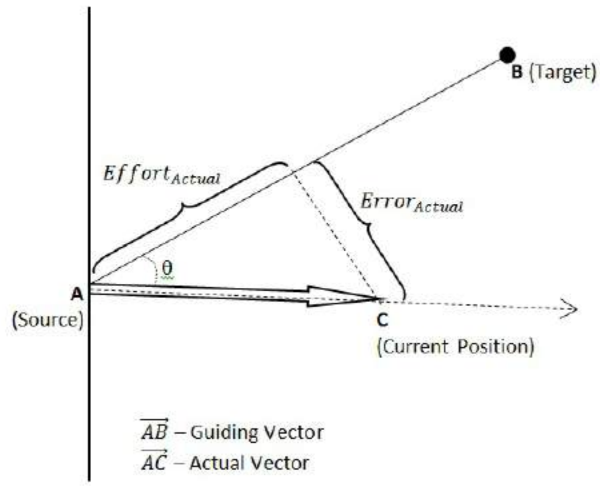


Figure 3.8: Representation of 'Guiding' and 'Actual' vectors and derivation of Effort and Error components

$|\overrightarrow{AB}|$ and $|\overrightarrow{AC}|$ are the magnitudes of the vectors $\overrightarrow{AB}$ and $\overrightarrow{AC}$ respectively

The MJT (Amirabdollahian et al., 2002) uses τ (see section 3.4.1.3) which is calculated using time t in order to return a position in the Cartesian space, so at any time between the start and end of a point-to-point reaching task, it is possible to obtain a position vector. Noting this, the line joining the source (point A) to the current position of the desired (MJT) path is termed as the MJT vector, the line joining the source (point A) to the current position (point C) achieved by the participant is termed as the actual vector and the imaginary line joining the source (point A) and the target (point B) is termed as guiding vector. Figure 3.8 and equations below show the derivation of Effort and Error components of the actual vector. $Effort_{Actual}$ is derived by projecting actual vector onto the guiding vector (line joining the source and target points) and $Error_{Actual}$ is derived as the extent by which actual vector is deviating from the guiding vector. $Effort_{MJT}$ and $Error_{MJT}$ are similarly calculated using MJT vector and the guiding vector.

ΔEffort: In order to compare the progress achieved by the robot and the participant a new parameter $\Delta Effort$ was calculated as follows:

$$\Delta Effort = Effort_{MJT} - Effort_{Actual} \tag{3.2}$$

Hypothesis

The effort contribution by the participant ($Effort_{Actual}$) when greater than the effort contribution by the robot ($Effort_{MJT}$), the participant is in lead of the activity and vice-versa.

3.5.1.3 Methods

As part of the vector space analysis, Exp-I was designed to investigate the Effort and Error contributions by the participant/robot during an interaction. Apart from informing the lead-lag role of the participant, vector space analysis could also inform about the deviation of the participant from the desired path through 'Error' parameter. The VR environment was enhanced to reflect these parameters. Presenting the 'Effort' and 'Error' components in VR environment would serve as a feedback to the participant and also helps in correcting the movement deviations if any.

The experiment was conducted in two phases *training phase and actual-performance phase* similar to the pilot study. See Section 3.4.1.2 for a detailed description of experimental protocol.

During the passive mode the participants were instructed to remain passive (i.e., not to exert any force on the HM's end-effector) and follow the robot which executed the entire movement from the source point to the target point of various segments. The Haptic API supplied with the HM facilitates in creating virtual effects in the workspace of the robot like a virtual spring or a virtual damper. The spring can be created at any specified 3D positions in the HM's workspace and with different stiffness levels. The damping coefficients specified to create a virtual damper, can damp the movement velocities in the 3D workspace.

The virtual spring-damper combination can produce an elastic band effect, termed as bead-pathway concept, (see Figure 3.9) that would restrict deviations of the arm movement along a specified trajectory. The trajectory between any two points in the HM's workspace was determined by the minimum jerk polynomials (Amirabdollahian et al., 2002) (Refer (Amirabdollahian, 2003) for more information on the bead-pathway concept). Using various combinations of spring stiffness levels and damping coefficients, different levels of guidance and correction could be defined.

As a consequence of using virtual spring-damper combination to propel the arm along the trajectory between two points, the actual trajectory achieved by the participant lags the MJT trajectory when the participant remains passive. Hence passive mode was chosen for testing the lagging performance. Similarly the participant was asked to overtake the robot during the AA2 mode to reach the target quickly and hence this mode was considered for testing the leading performance of the participant.

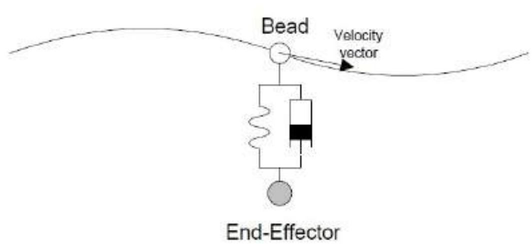


Figure 3.9: Spring-damper combination used to guide the user over the reference trajectory
Image courtesy Dr. Farshid Amirabdollahian

3.5.2 Results and Analysis

The data recorded from the 'actual performance phase' was used for data analysis purposes. Figure 3.10 shows the organisation of the raw data for analysis.

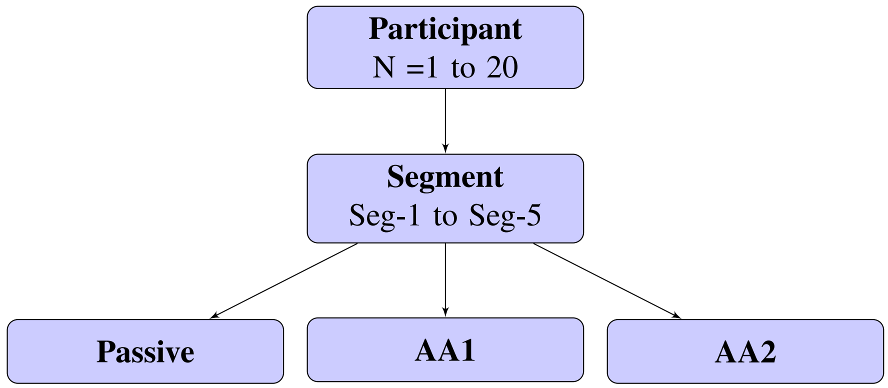


Figure 3.10: Raw-data organisation for Exp-I

Table 3.3: Participant's role and corresponding testing condition (Exp-I)

Mode	Participant's role	Testing condition
Passive	Lagging	$\Delta Effort > 0$
AA2	Leading	$\Delta Effort < 0$

3.5.2.1 Segment specific analysis

The $\Delta Effort$ parameter, according to Equation 3.2 was expected to remain positive in the passive mode, as the participants were instructed to remain passive during this mode. The $\Delta Effort$ parameter was expected to be negative during the AA2 mode, as the participants were asked to overtake the robot and lead the activity. Therefore the hypothesis for our data analysis was whether it is possible to use the sign for the $\Delta Effort$ in order to identify participant's leading or lagging role (see Table 3.3).

Our first step of data analysis was to check the spread of the $\Delta Effort$ parameter during each segment performed under different modes. Segment wise graphs of tau (τ) vs $\Delta Effort$ were plotted with each plot showing a different patterned- coloured line for different modes (Passive, AA1 and AA2). Figure 3.11 and Figure 3.12 show the plots for Participant 15 during various segments. Similar results were observed for other participants.

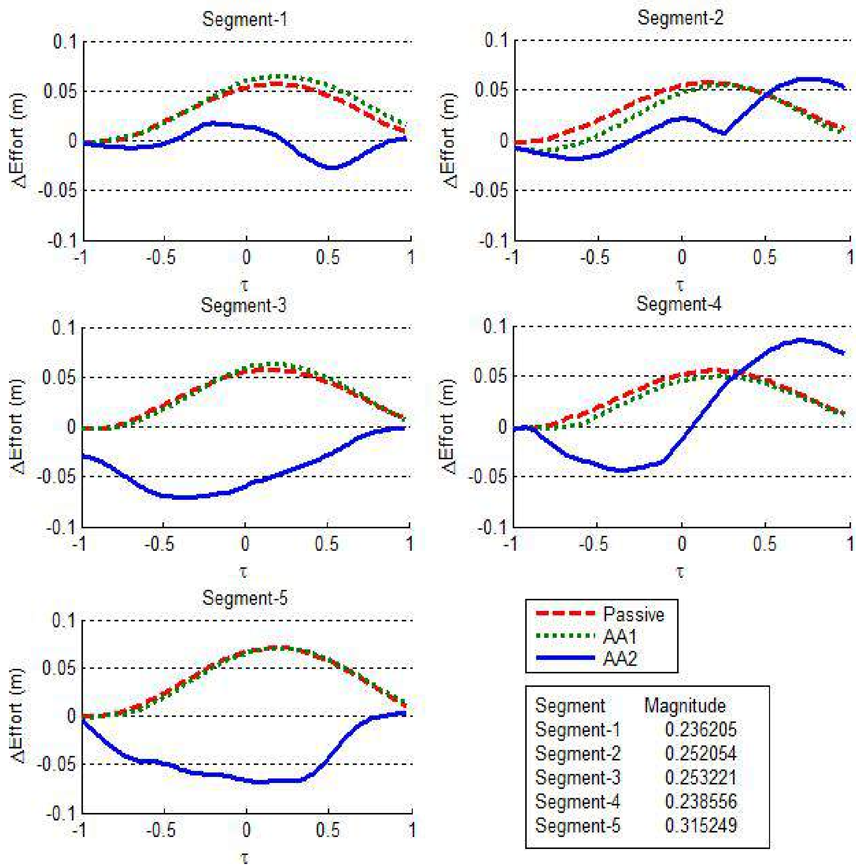


Figure 3.11: Tau (τ) vs $\Delta Effort$

Figure 3.11 shows that $\Delta Effort > 0$ was satisfied during the passive mode for all the five segments, while during the AA2 mode $\Delta Effort < 0$ was satisfied during segments 3 and 5 and the major part of segment 1, but during segments 2 and 4, $\Delta Effort$ showed a varying pattern as tau progressed from -1 to 1. To explore this further, for all samples during the AA2 mode we computed the summation of $\Delta Effort$ for each segment that could indicate if $\Delta Effort$ remained negative for major part of the segment. Therefore the new testing condition for leading performance of the participant was formed as shown in Table 3.4 on page 69.

Figure 3.13 on page 69 illustrates the number of participants (out of 20 participants

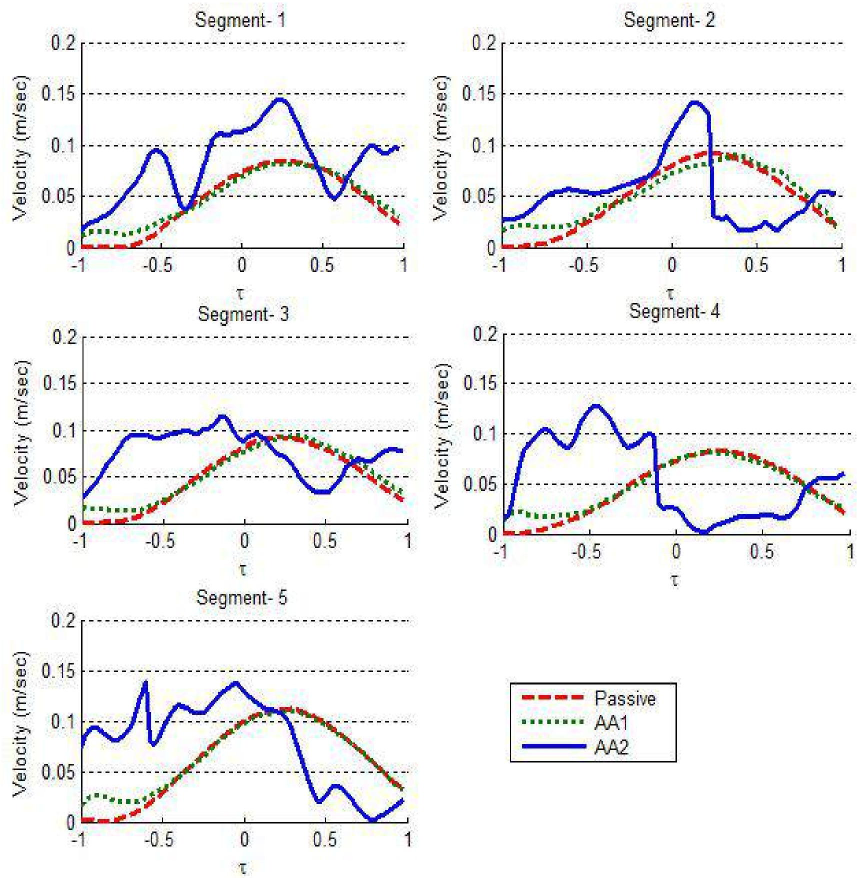


Figure 3.12: Tau (τ) vs Velocity

who took part in the study) satisfying the leading performance condition during various segments of the AA2 mode. It is clearly evident from the figure that during segments 1, 3 and 5 $\geq 50\%$ of the participants satisfied the leading performance conditions while during segments 2 and 4 the count was $\leq 40\%$. To examine if this difference identified between various segments was dependent on the length of the segment (segment lengths are summarized in a box at the bottom right of Figure 3.11), we conducted a correlation test between magnitude of segments and the number of participants that managed to lead the performance during those segments, but no significant correlations were found. The velocity plots in Figure 3.12 show a smooth pattern during the Passive and the AA1 modes compared to a visibly multi-peak velocity during the AA2 mode. This indicated that par-

Table 3.4: Participant's role and corresponding testing condition (modified) (Exp-I)

Mode	Participant's role	Testing condition
Passive	Lagging	$\sum_{i=1}^{n} \Delta Effort > 0$
AA2	Leading	$\sum_{i=1}^{n} \Delta Effort < 0$

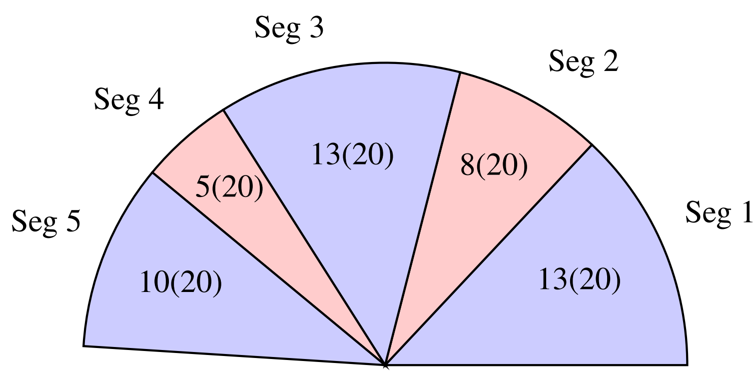


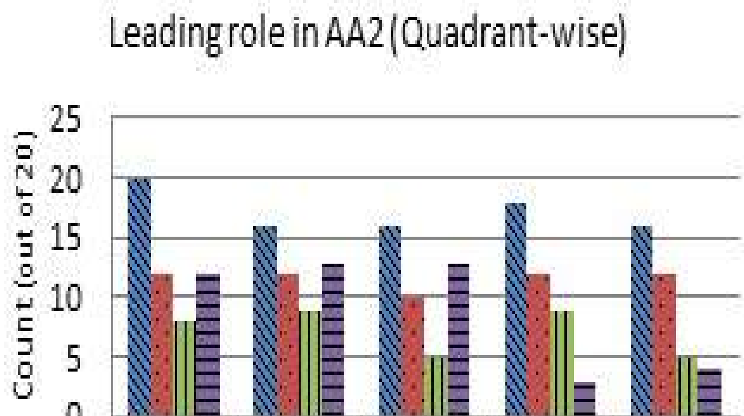
Figure 3.13: Number of participants out of 20 satisfying leading condition during the five segments of AA2 mode.

ticipants actively contributed during the AA2 mode, yet did not manage to lead the robot in achieving the task goals. It was notable from Figure 3.1 and Figure 3.2 that segments 1, 3 and 5 were reaching segments where the movement started at a source point located closer to the participant's body and ended at the target point away from the body. Segments 2 and 4 were returning segments where the movement started at a source farther away from the participant's body towards a target closer to the participant's body. Our observation here indicated that in cases where the robot moved towards the participant's body, the participants often failed to lead the interaction.

3.5.2.2 Quadrant specific analysis

It was identified that a very low number of participants could lead the interaction during segments 2 and 4 (returning segments) of the AA2 mode. Also, plots of segments 1, 2 and 4 in Figure 3.11 showed that the sign of $\Delta \mathit{Effort}$ did not remain constant as tau progressed from -1 to 1. A possible cause was linked to the duration set to execute a segment and whether there was enough time allocated to perform a segment comfortably. The segments were therefore fragmented into four equal quadrants (based on τ) to carry out a closer observation of lead-lag role of the participant during various segments of the AA2 mode. The four quadrants were formed as follows: Quadrant-1 (Q1, $-1 \leqslant \tau < -0.5$), Quadrant-2 (Q2, $-0.5 \leqslant \tau < 0$), Quadrant-3 (Q3, $0 \leqslant \tau < 0.5$) and Quadrant-4 (Q4, $0.5 \leqslant \tau \leqslant 1$). The decision to divide the segments into four equal quadrants was solely based on the literature and the expectation of a bell-shaped velocity profile during these segments (Morasso, 1981; Abend et al., 1982; Flash et al., 1985; Amirabdollahian, 2003). Our anticipation was that if duration is an influencing parameter, there will be a gradual reduction of participant numbers managing to lead the robot as one progressed from Q1-Q4. The condition for the leading role was then applied to all four quadrants of each segment and the number of qualifying participants that led the interaction during that quadrant was counted.

The results were presented by the bar chart (Figure 3.14). Reaching segments (1, 3 and 5) show similar patterns with $\geqslant 50\%$ participants satisfying the leading performance condition during Q1, Q2 and Q4 and $< 50\%$ during Q3. Similarity also existed in returning segments (2 and 4) with $\geqslant 50\%$ participants satisfying the leading performance condition during Q1 and Q2 and $< 50\%$ during Q3 and Q4. This showed that during Q1 and Q2 the majority of the participants could lead the performance during all segments in the AA2 mode when they were asked to do so, but the lead role was not consistent during Q3 and Q4. It further highlighted that there was potentially a link between the type of reaching task, its set duration and the participant's ability to lead during an active assisted interaction.



	Seg-1	Seg-3	Seg-5	Seg-2	Seg-4
Q1	20	16	16	18	16
Q2	12	12	10	12	12
Q3	8	9	5	9	5
Q4	12	13	13	3	4

Figure 3.14: Quadrant specific counts of subjects satisfying leading condition in the AA2 mode during various segments.
Segments were re-ordered to allow for better comparison

3.6 Discussion

During Exp-I the duration to execute each segment was set to 4 seconds. Data analysis results showed that the participants did not always lead the robot when they were asked to do so in the AA2 mode. When the segment was further fragmented into quadrants, the results showed the leading role in Q1 and Q2 and an inconsistent role in Q3 and Q4 in the majority of the cases. A likely explanation for this behaviour is that participants were restricted from performing at their normal and natural pace by the pre-set 4 seconds duration while segment lengths and arm movement patterns varied. It could also be linked to the type of movement (reaching away or returning towards the participant's body) required for executing each segment. Also, Figure 3.2 shows that reaching segments (1, 3 and 5) had a more pronounced gravity component towards Q3 and Q4 while returning segments (2 and 4) present the opposite. This gives rise to the question whether movement direction influences the performance of the participant which needs to be tested.

The research by J Dewald et al at Northwestern University using the ACT^{3D} (see details of ACT^{3D} under section 2.5 for further details) (Ellis et al., 2007; Ellis et al., 2009) showed that various levels of limb loading influenced the muscle synergies and thereby reaching range on motion. While these results were from the studies conducted with stroke sufferers where there is an expected abnormality in muscle synergies, our studies were with healthy users. All the reaching segments executing during our studies were against gravity and all the returning segments were towards gravity. In order to further explore the influence of gravity on the movement patterns with healthy users, including various combinations of reaching-returning segments that are towards-against gravity was considered for our further studies.

Our findings from Exp-I further emphasized the need for adaptive interaction as they indicated that different movement patterns require different settings. An interesting question here is whether a customised duration is sufficient to pose a therapeutic challenge? One logical approach was that the duration for performing segments should be based on participants' natural pace/requirement which needs further investigation.

3.7 Chapter summary

The studies presented in this chapter demonstrated that the leading-lagging performance of the participants could be identified using the positional coordinates recorded during a HRI session. Robots often use a reference trajectory model to guide the movement of patients. The error between the robot recorded coordinates and the reference trajectory coordinates at a given time was used to identify the lead-lag contribution of the participant interacting with the system.

The results with single axis or planar (horizontal XY plane) point-to-point movements during a pilot study (PS-I, see Section 3.4) showed that the sign of the error was impacted by the type of movement (reaching away or returning towards the body) and also by the introduction of elevation into the experimental workspace. These findings were further explored in a 3-dimensional workspace in our next study (Exp-I, see Section 3.5), during which scenarios were created where the participants were asked to intentionally lead or lag the interaction using feedback provided by the graphical user interface, while the robot was programmed to follow the MJT. Results from Exp-I showed that vector projections of positional data recorded could inform about the lead-lag role of the participant. However, it was observed that participants were not always successful in leading the interaction when they were asked to do so. Leading performance was often achieved during the 'reaching' segments while participants often failed to lead during the 'returning' segments. This study highlighted that while identifying lagging or leading role of the participant is now possible, it is important that participants are provided with a setting which would allow them to achieve lagging or leading requirements. Such an adjustment will result in personalising the experiment to each participant's requirements. Therefore investigations into the usefulness of $\Delta Effort$ (identified by Exp-I) as a performance indicator to adapt the GENTLE/A system to user's requirement formed the key part of our further research.

Chapter 4

Adaptive algorithm I

4.1 Introduction

The results from our previous study (PS-I, see Section 3.4) showed that positional lead-lag could successfully identify the role of the user interacting with the GENTLE/A system during single axis or planar (horizontal XY plane) point-to-point movements. But the sign of the positional lead-lag was impacted by the type of movement (reaching away or returning towards the body) and also by the introduction of elevation into the experimental workspace. This prompted a move into vector space where the lead-lag identification would become independent of the direction of the movement.

The findings from PS-I were further tested in 3-dimensional workspace using vector projections in Exp-I (see Section 3.5). It was observed that participants were not always successful in leading the interaction when they were asked to do so. Participants could lead the interaction during the 'reaching' (moving away from the body), but could not always lead the interaction during the 'returning' (returning towards the body). The set of points that were chosen for these previous studies were spread out in the 3D workspace of the HM, but during all the reaching segments, the movement was against gravity and during all the returning segments, the movement was towards gravity. Investigations into reasons underlying our observations led to some interesting conclusions which are detailed in section 4.2. Section 4.2 also discusses the aims of this study and how the main research questions were addressed. Our intention was to adapt the robot so that it could tune according to the role of the interacting participant. Section 4.3 presents the algorithm proposed to adapt the GENTLE/A system according to the lead-lag role of the participant, and describes the details of the experiment conducted to evaluate the algorithm. The results from the experiment are presented in section 4.4 and the influence of various input parameters on the adaptive nature of the system was assessed using the regression model. The applicability of the algorithm in clinical settings is discussed in the following section.

4.2 Research Questions

The parameter Δ*Effort* was identified by Exp-I as a potential performance indicator. Results from Exp-I also highlighted the situations when Δ*Effort* indicated the lead-lag role of the participant against the expected role. The possible reasons for these findings are discussed in this section. The section also describes aims of Exp-II to further explore these findings from Exp-I and finishes by discussing how these aims address the main research questions.

Type of movement

The *Segment specific analysis* (see Section 3.5.2.1) from Exp-I highlights that the type of the movement (reaching/returning) was influencing the performance of the participant. The set of points chosen during Exp-I was such that all the reaching away from the body segments were against gravity and all the returning towards the body segments were towards the gravity. The direction of movement (away/towards) with respect to gravity could be influencing the performance, as the participant's arm was not gravity compensated.

In order to investigate the influence of gravity on the performance of the participant, Exp-II used a set of points chosen such that different combinations of reach-return and ground level-against gravity-towards gravity movements were executed during the experiment.

Duration

During Exp-I the participants were given a constant duration of 4s to execute any segment. The set of points, duration of 4s to execute a segment and a delay of 3s between any two consecutive segments were chosen from the GENTLE/S database. The *Quadrant specific analysis* (see Section 3.5.2.2) from Exp-I identified that the duration given to execute a point-to-point movement could have influenced the lead-lag role of the participant. The duration given was either too short and did not allow the participant to lead the interaction or too long and led to a lazy performance of the participant.

In Exp-II the adaptive algorithm would adapt the duration given to execute a point-to-point movement to reach an optimum value duration according to the performance of the participant.

Embedded vs Virtual

The depth perception in the virtual environment presented in the previous experiments was felt difficult by the participants. A virtual 3D scenario like a 3D screen or 3D glasses to be worn by the user were discussed as options to improved the VR. Considering the future use of the system with stroke patients who usually suffer from visual neglect after stroke, the options of virtual 3D scenario were not taken further. Therefore during Exp-II the virtual environment was slightly modified to enhance the depth perception and an embedded set-up was also introduced. Embedded set-up allows to incorporate real objects or cues into the workspace while their positions correlate with the position of virtual objects on the screen. This was to study the performance of the participant in the presence/absence of a real object alongside the virtual object displayed on the screen. The embedded and virtual environments are described in detail in Section 4.3.1.

Exp-II aimed to address RQ2 and RQ3 of our research with the GENTLE/A rehabilitation system:

RQ2: Can this role identification be further utilised as a performance indicator?

Exp-II used Δ*Effort* as a performance indicator and was so designed to create situations where Δ*Effort* indicated the role of the participant against the one expected during Exp-I. The findings from Exp-I were further explored during Exp-II to evaluate the usefulness of Δ*Effort* as a performance indicator.

RQ3: How can the performance indicators be used to improve the adaptability of the GENTLE/A rehabilitation system?

The adaptive algorithm that was evaluated during Exp-II uses Δ*Effort* to identify the leading/lagging role of the participant and would adapt the duration given to execute a point-to-point movement to reach an optimum value according to the performance of the participant.

4.3 Experiment (Exp-II)

4.3.1 Experimental set-up

The experimental set-up for this study remained the same as that of Exp-I but for a replacement of the ring gimbal with a ball gimbal (see black ball in Figure 4.2). The ring gimbal facilitated the patients who were lacking the ability to grasp to train with the GENTLE/S rehabilitation system during the clinical trials. As Exp-II was designed to be conduced with healthy participants the ring gimbal was replaced with a ball gimbal. The participants were asked to hold the ball attached to the end of the robotic arm (see Figure 4.2) with their dominant hand and move between various points displayed on the monitor. Due to constraint of time, data was only recorded with dominant hand during the experimental sessions. Recording data with both dominant and non-dominant hands that could facilitate comparison of the performances was left for future investigations.

Points on Cube

Figure 4.1 shows the VR set-up with cube and balls. The green balls represented the source and target points for various segments. The cube was formed such that points on the cube facilitate different combinations of movements including reach-return, ground level-against gravity-towards gravity, etc.

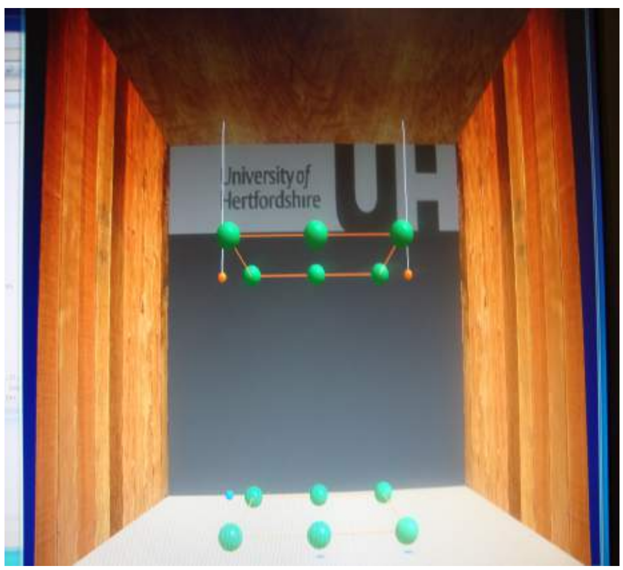


Figure 4.1: Virtual environment

Embedded vs. Virtual

Previous research in our group tested the performance of participants in environments with different levels of realism (Bowler et al., 2011). Results showed that participants performed better in an embedded reality setting when compared to a purely virtual setting. In order to facilitate the comparison of the participants' performance in the presence/absence of an embedded object, an embedded reality set-up was created. Figure 4.2 shows both the embedded and the virtual targets. Help from an embedded object was provided for some points and other points only had a virtual representation. Ping-Pong balls were either hung from the top frame or placed on the table-mat at a small elevation, in close proximity to the virtual balls of the cube, to provide assistance for depth perception. With respect to the points located on the front face of the cube that were closer to the participant, visible stickers were placed on the table-mat, just below the positions where the actual points of the cube exist in the workspace. The positions of the embedded objects were chosen to be closer to the virtual objects but not an exact match so that, (i) the embedded objects would not interfere with the visibility of the virtual objects displayed on the screen and (ii) to minimize the physical contact between the participant's arm and the embedded object and thereby minimize the calibration errors during an experimental session.

Figure 4.2: Embedded set-up (showing both Virtual targets (on screen) and real targets (Ping-Pong balls and stickers on the table mat))

Modes of operation

The HM was programmed to operate in two modes for the purpose of this experiment.

1. *Passive:* Participant passive robot active
2. *Active-assisted:* Participant and robot work together

The passive and the active-assisted modes were chosen to test the lead-lag contribution of a participant during a human-robot interaction session, as robot was often active during these modes.

Lead-Lag scenarios

Lagging performance: During the passive mode the participant was asked to remain passive (i.e., not to exert any force on the HM's end-effector) and the robot was programmed to execute the activity according to the MJT. During the execution of a segment, at the beginning of every sampling interval, the MJT position was computed and then the robot gently pulled the participant's arm to catch up with the MJT position. Given the instructions to the participant to remain passive, the passive mode was chosen for studying the 'lagging' performance of the participant.

Leading performance: In the active-assisted mode the participant had to initiate the activity and subsequently the participant and the robot could work in coordination to finish the activity. The HM was programmed to follow the MJT. This was the first repetition of the active-assisted mode and was termed as AA1. In the second repetition of the active-assisted mode (AA2), the participant was encouraged to use additional force to pull the robot arm to reach the target point quicker than the set duration, thus surpassing the speed of the robot. Hence AA2 was considered for studying the 'leading' performance of the participant. Figure 4.3 shows a pictorial representation of lagging and leading scenarios which was used to provide feedback to participants during their lagging and leading performances.

A virtual spring-damper combination created at the HM's end-effector produced an elastic band like effect restricting the movement of the arm along the reference trajectory (refer section 3.5.1.3 for more details). The deviation (or error) allowed from the reference trajectory was defined by the stiffness of the virtual spring. During this study the stiffness was set to constant value of 250 N/m for the entire experimental session, hence it is assumed that the effect of stiffness remained the same during both leading and lagging scenarios.

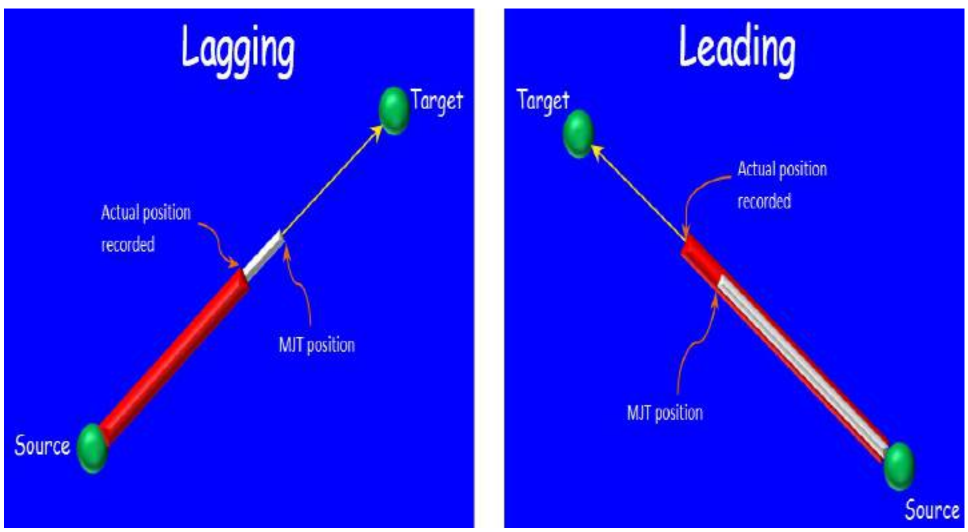


Figure 4.3: *Leading* and *Lagging* scenarios

4.3.2 Participants

Thirty-two healthy participants took part in the experiment, age range 33.6 ± 9.4 (mean ± standard deviation), including 18 female and 14 male participants. Written informed consent was obtained from each participant before inclusion in the studies and ethical approval of the evaluation protocol was obtained from the University's ethics committee (under University of Hertfordshire approval number 1112/45).

Data from two participants (Participants 28 and 29) remained fluctuating throughout the experiment, possibly due to the participants' inability to master how to perform the task at hand. Hence the data recorded from these two participants was excluded from analysis. The data collected from thirty participants (n = 30) was used for the analysis purposes.

4.3.3 Experimental protocol

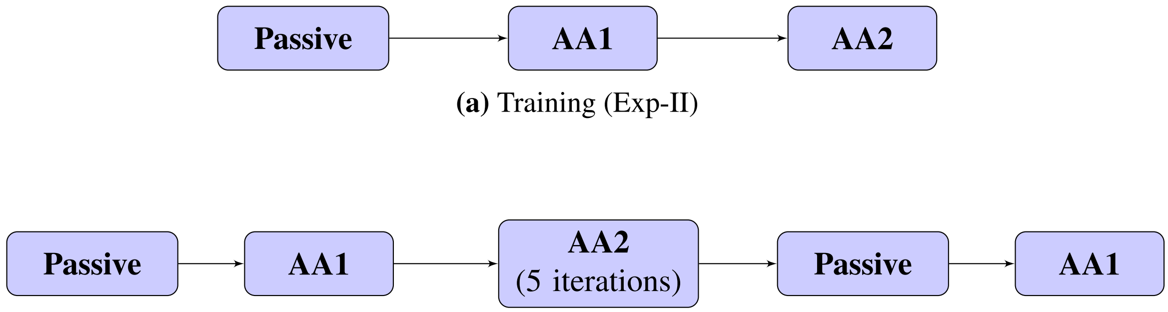
The experiment was conducted in two phases: (a) Training, (b) Actual-Performance. Figure 4.4 shows a flow-chart style representation of the experimental protocol. During both phases, participants held the gimbal (see black ball in Figure 4.2) to follow or lead the robot in its trajectory.

I. *Training:* In the training phase each mode (passive, AA1 and AA2) was executed at least once or a few times until the participant became familiar with the operation.

II. *Actual-performance:* The participants executed the passive and the AA1 modes twice, at the beginning and then at the end of the actual-performance phase. The AA2 mode was executed five times during which the system attempted to adapt according to the algorithm implemented that used the interaction parameters recorded. The participants executed thirteen segments in every mode following the same sequential order.

4.3.4 Adaptive algorithm I

As $\Sigma(\Delta Effort)$ was the parameter indicative of the lead-lag role of the participant, the contribution of the participant during any interaction session was assumed to be proportional to this parameter. The algorithm below shows how the duration given to execute a segment was adjusted at the end of each AA2 repetition. The next repetition of AA2 mode



(a) Training (Exp-II)

(b) Actual-performance (Exp-II)

Figure 4.4: Experimental protocol (Exp-II)

used the new duration and the process of duration adjustment according to the algorithm below repeated for all the five iterations of the AA2 mode executed during this study.

$$
\begin{gathered}
if \sum_{i=1}^{n} \Delta Effort_{Seg-k} > 0 \\
(duration_{Seg-k} + \delta) \\
else \\
(duration_{Seg-k} - \delta) \\
where\ \delta \propto \sum_{i=1}^{n} \Delta Effort_{Seg-k}\ and\ \delta \in [0.0, 1.0] \\
n\text{ - number of samples recorded during segment-}k
\end{gathered}
$$

This algorithm in effect increases the duration to execute a segment by a small amount (δ), that is proportional to the $\Sigma(\Delta Effort)$ which is calculated from the recorded interaction parameters, in case where the participant is lagging the reference trajectory. Similarly the duration is reduced by a small amount where the participant is leading the interaction. The proportion (δ) by which the duration is adjusted based on $\Sigma(\Delta Effort)$ is shown in Table 4.1.

4.4 Results and Analysis

One of the main aims of this study was to test the adaptability of the GENTLE/A system to tune the duration to execute a point-to-point movement. Therefore the first step of

Table 4.1: AA I adjusted duration by δ based on $\Sigma(\Delta Effort)$

$\Sigma(\Delta Effort)$	δ **(Leading)**	δ **(Lagging)**
$\lvert\Sigma(\Delta Effort)\rvert \leq 1$	0.0	0.0
$1 < \lvert\Sigma(\Delta Effort)\rvert \leq 2$	-0.2	0.2
$2 < \lvert\Sigma(\Delta Effort)\rvert \leq 3$	-0.4	0.4
$3 \leq \lvert\Sigma(\Delta Effort)\rvert$	-1.0	1.0

Table 4.2: Adaptation of segment duration for Participant 2 during the five iterations of the AA2 mode (Exp–II)

S1[a]	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**	**S11**	**S12**	**S13**
4	4	4	4	4	4	4	4	4	4	4	4	4
3.4	3	3	3	3.6	3.8	3	3.8	3.4	3	3	3.6	3
2.4	2	2.2	2	2.6	2.8	2	2.8	2.6	2.8	2	2.6	2
2.2	1.6	1.8	1.6	2.4	1.8	1.8	1.8	2.2	2.8	1.6	2.2	1.6
1.6	1.6	1.6	1.2	2.4	1.6	1.6	1.6	2	2.6	1.2	2	1.6
1.8	1.6	1.6	1	2.4	1.6	1.6	1.6	1.8	2.6	1	2	1.6

[a] S1 -Segment-1, S2 -Segment-2 and so on

data analysis involved studying the pattern in which the duration for each segment varied through repetitions of the AA2 mode. During the experiment the participants executed thirteen segments traversing between different points presented in Figure 4.1 on 79. Table 4.2 demonstrates the pattern in which the segment duration varied for one of the participants (Participant 2).

Constant optimum duration rule:

If the duration remained constant for two or more iterations without a further change as the iterations progressed, we considered the duration to have reached a constant optimum value for that segment.

Applying the above rule, it can be observed from Table 4.2 that nine out of thirteen segments reached a constant optimum duration within five iterations of the AA2 mode for Participant 2.

Table A (presented in Appendix I) shows the pattern of duration change during the five iterations of the AA2 mode for all the participants of the study. It can be observed from the table that in general the duration always progressed downwards from the default duration set at the beginning of the five iterations. This table was studied further from two view points,

(1) *Iteration level:* The variations in the number of iterations required in reaching a constant optimum value of duration from participant to participant.

(2) *Segment level:* The variations in the number of participants reaching a constant optimum value of duration for different segment.

4.4.1 Iteration level analysis

The first observation from the table was the number of segments that reached a constant optimum duration within the five iterations of the AA2 mode for each participant. Figure 4.5 shows that the number of segments that reached a constant optimum value of duration within five iterations of the AA2 mode varied across participants. It could also be observed from Table A (in Appendix I) that for some of the participants, few segments reached a constant value within the first 2-3 iterations, and entered a varying duration phase again in the later iterations. The best possible explanation for this change could be that participants aimed to outperform the robot during the later iterations. During the AA2 mode, which is the testing condition for the leading scenario, the participants were asked to use additional force to lead the robot, so although the participants reached their comfortable duration in the first 2-3 iterations, they tried to push themselves harder to outperform the robot and this could have led to further changes in the duration. As healthy volunteers, the participants kept trying to outperform the robot and the system continued to adapt the duration through this process which indicated the adaptability of the GENTLE/A system.

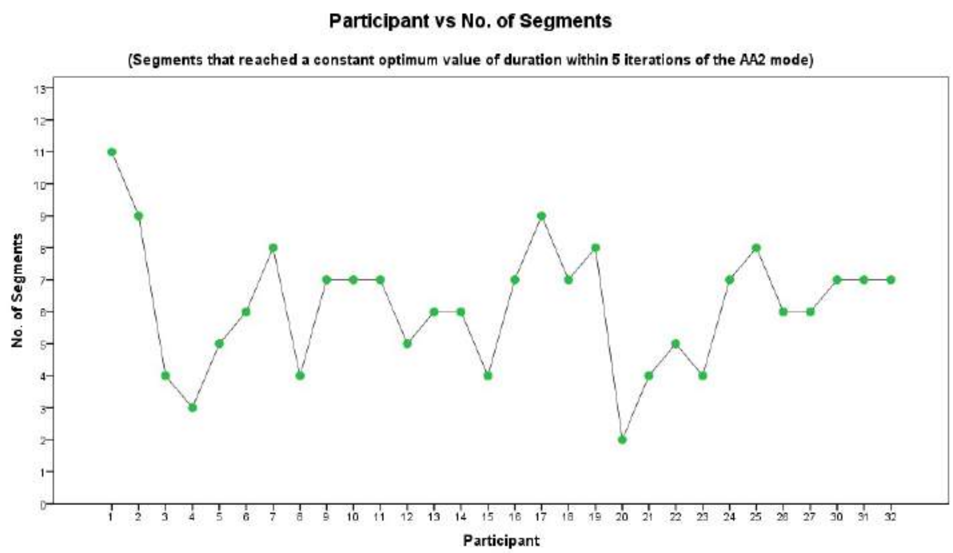


Figure 4.5: Line chart representation of number of segments that reached constant optimum value of duration for every participant within the five iterations of the AA2 mode

4.4.2 Segment level analysis

The second observation concerned varying number of participants reaching a constant optimum value of duration during different segments. It can be observed from Figure 4.6 that for segments 8 and 11, nineteen out of thirty participants reached a constant optimum value of duration within five iterations. During segment 7 the measure was (18/30) and the measures for other segments were lower: segment 4 (16/30), segments 5 and 12 (15/30), segments 1 and 9 (14/30) and for rest of the segments (bars in 'red') even lower.

The key observation of pattern change in durations during the five repetitions of the AA2 mode was, the default duration set at the beginning of the first repetition almost always scaled down during all the segments for all the participants by the end of the five repetitions. The patterns observed at *iteration level* and *segment level* inform that the number of repetitions required to reach a constant optimum value of duration should be personalised. In addition the patterns observed at *segment level* led to the investigation of any underlying patterns in the execution of various segments and forms the major part of the results and analysis from Exp-II.

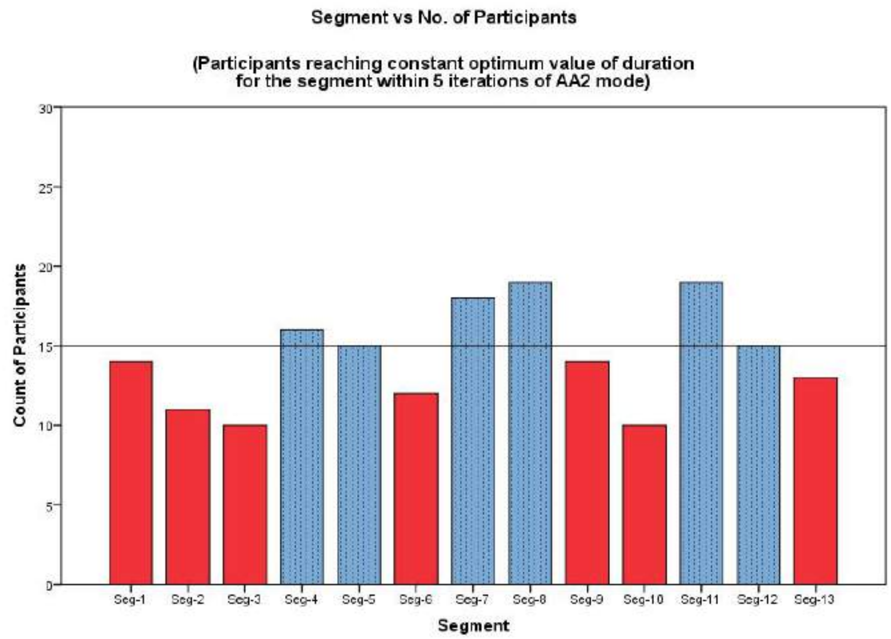


Figure 4.6: Bar chart representation of number participants reaching a constant optimum value of duration during each segment within the five iterations of the AA2 mode

The thirteen segments executed by the participants varied in length. Among these segments, few segments had an embedded object closer to the target point in addition to the target point displayed as a green ball on the monitor (virtual object). Some segments required a reaching movement (moving away from the body) and some required a returning movement (moving towards the body). The first four segments were executed at ground level without the requirement to move against or towards gravity, while the rest of the segments either moved towards ground or away from it.

In addition the segments also differed in terms of the movement across the body i.e., from one side of the participant's body towards the other side. The movement across the body is referred to as 'cross-body movement' through the rest of this analysis. Observations by the experimenter during the study showed that the segments that involved larger magnitude of cross-body movement were perceived difficult to execute when compared

Table 4.3: Segment Details - listing various input conditions (Exp-II)

Segment	**Length (m)**	**Condition-I Embedded-Virtual**	**Condition-II Reach-Return**	**Condition-III Movement direction**	**Condition-IV Cross-body movement**
Seg-1	0.350	Embedded	Reach	Ground-level	Large
Seg-2	0.320	Embedded	Return	Ground-level	Small
Seg-3	0.320	Virtual	Reach	Ground-level	Small
Seg-4	0.350	Virtual	Return	Ground-level	Large
Seg-5	0.415	Embedded	Reach	Against Gravity	Large
Seg-6	0.400	Embedded	Return	Towards Gravity	Small
Seg-7	0.400	Embedded	Reach	Against Gravity	Small
Seg-8	0.415	Embedded	Return	Towards Gravity	Large
Seg-9	0.276	Virtual	Reach	Against Gravity	Large
Seg-10	0.415	Virtual	Reach	Towards Gravity	Large
Seg-11	0.400	Virtual	Return	Against Gravity	Small
Seg-12	0.400	Embedded	Reach	Towards Gravity	Small
Seg-13	0.415	Virtual	Return	Against Gravity	Large

to segments with smaller magnitude of cross-body movement by majority of the participants. Therefore, alongside the first three conditions listed in Table 4.3, a fourth condition describing the cross-body movement involved during every segment was also included in the data. Table 4.3 lists the lengths of all the segments and various conditions imposed during these segments. Figures 4.7 - 4.9 give a pictorial representation of the thirteen segments, Figure 4.7 shows the top-view of the segments executed at 'ground level', Figure 4.8 shows the segments that were 'against gravity' and Figure 4.9 shows the segments that were 'towards gravity'. In these figures the 'reaching' segments were identified by blue lines and the 'returning' segments by red dotted lines. The ground level segments were executed in a horizontal XY plane with lowest possible Z-axis positions of the HM's workspace, the influence of gravity was therefore assumed to be a constant (minimum) value during these segments.

In order to facilitate the comparison of performance of the participants during different

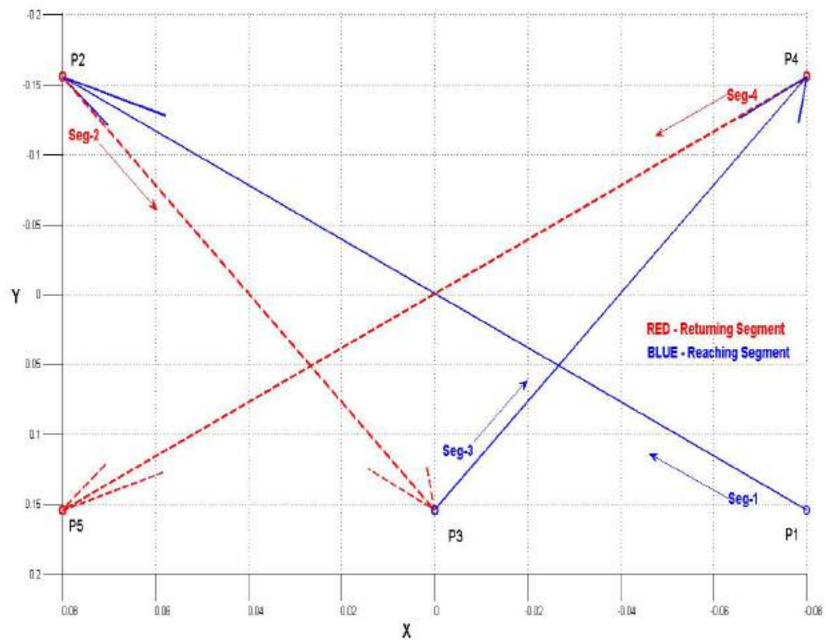


Figure 4.7: Segments (Ground Level) - Segments 1, 2, 3 and 4 executed at ground level (horizontal XY plane).

segments, the duration to execute a unit length of a segment was calculated as below and it was called 'Normalised duration'.

$$\textit{Point A (source):}\ (A_x, A_y, A_z)$$

$$\textit{Point B (source):}\ (B_x, B_y, B_z)$$

$$\textit{Segment Magnitude} = \sqrt{(B_x - A_x)^2 + (B_y - A_y)^2 + (B_z - A_z)^2}$$

$$SegmentDuration_{Normalised} = \frac{SegmentDuration_{Recorded}}{SegmentMagnitude}$$

The study is aware that different patterns for arm movements might include activities of different muscle groups and different muscle synergies. In this study, we chose to investigate the lagging and leading attributes of movements in spite of this variation. The study of influence of different muscle groups in performing various segments forms part of our future investigations with data collected from this study.

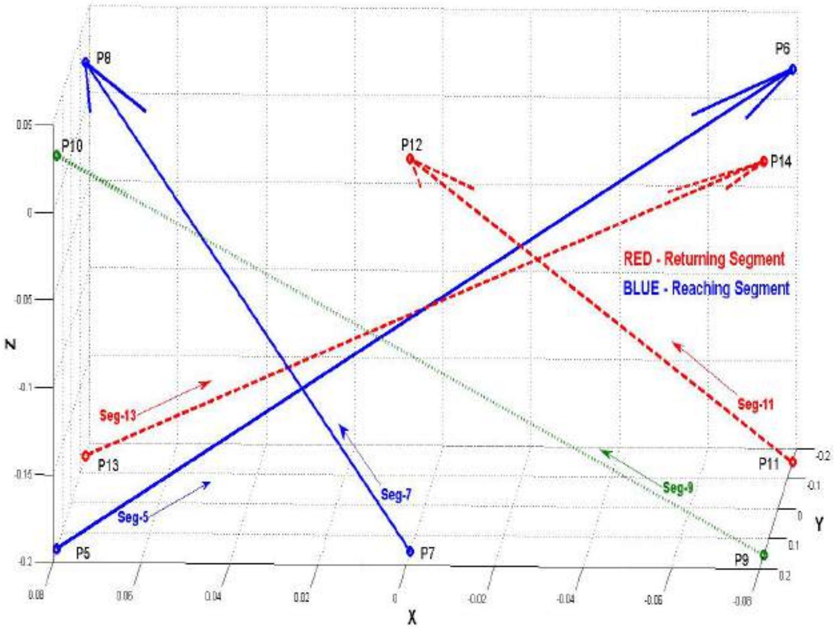


Figure 4.8: Segments (Against Gravity) - Segments 5, 7, 9, 11 and 13 executed against gravity.

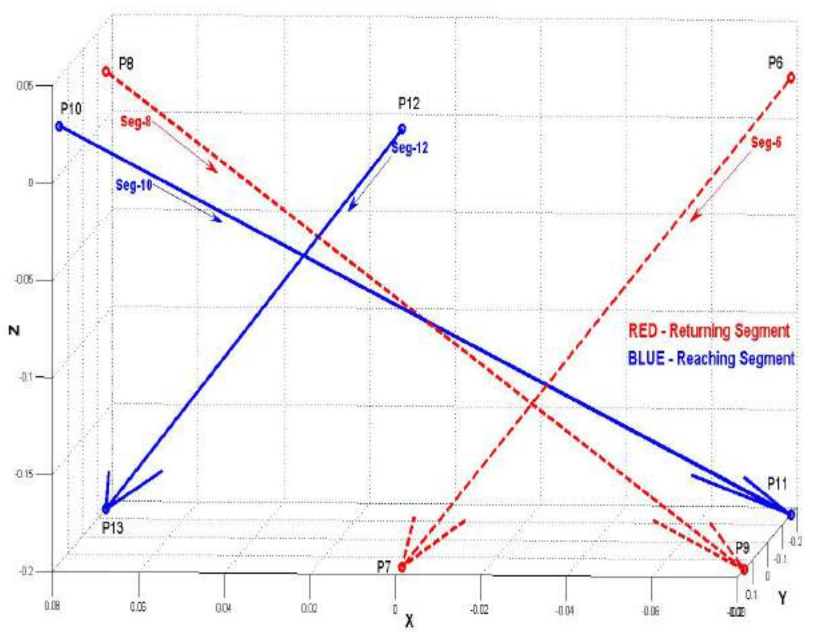


Figure 4.9: Segments (Towards Gravity) - Segments 6, 8, 10 and 12 executed towards gravity.

Multivariate Regression Analysis

Our goal was to study the variations in duration to execute a segment based on the set of conditions imposed to execute a segment. Hence regression was chosen as a suitable model, with duration to execute a segment as the outcome variable and set of conditions as predictors (Field, 2005). Similar analysis was performed previously on the data from the GENTLE/S clinical trials using multiple linear regression (Amirabdollahian et al., 2007). The regression was carried out using IBM SPSS 21.

The nature of various segments executed during the experiment differed in four conditions, Condition-I (Embedded-Virtual), Condition-II (Reach-Return), Condition-III (Against Gravity-Towards Gravity-Ground level), Condition-IV (Small-Large cross-body movement). Table 4.4 provides the details of the categories under all the four conditions that are used as dummy (or predictor) variables in the regression. In order to study if the outcome variable (duration) of the regression model was considerably influenced by any of the participants, participants were also introduced as predictors into the regression model. The final list of predictors used for regression analysis can be found in Table B (in Appendix I). The process detailed in (Hardy, 1993) was used as reference in creating dummy variables for the regression model.

Model 1:

The categories under all four conditions were keyed in as predictors into the regression model. Similarly participants were also included as predictors. Participant 1 was considered as reference participant in the regression model, as Participant 1 had greatest number of segments (11 out of 13) reaching to a constant optimum duration within the five iterations of the AA2 mode among all the participants of the study. The reference categories and the outcome variable (duration) remained the same for all the regression analysis models.

Table 4.4: Categories under four conditions used as dummy variables for regression

Condition	Categories (Symbol)[a]
Condition I	**Virtual (EV0)** Embedded(EV1)
Condition II	**Return (RR0)** Reach (RR1)
Condition III	**Against Gravity (G0)** Towards Gravity (G1) Ground Level (G2)
Condition IV	**Large cross-body movement (CB0)** Small cross-body movement (CB1)

Table 4.5: Descriptive Statistics for dependent variable (Regression results)

Dependent Variable	Mean	Std. Deviation	N
Duration	8.582	2.706	2432
N - Number of cases			

Model 2:

Model 1 assumed that various conditions imposed during a segment independently influenced the performance of the participant. In order to investigate whether the influence of various conditions was mutually exclusive or had a combined effect on the performance of the participant interaction variables were created (as explained in Hardy, 1993). Regression was run the second time with interaction variables included as additional predictor variables. The results from the first two regression models are reported in Table 4.5, Table 4.6 and Table B (presented in Appendix I).

R Square (R^2) and Adjusted R^2

R^2 (=0.651 for Model 2) implies that 65.1% variability in the outcome of dependent variable is accounted for by the dummy variables (predictors) that are included in the re-

Table 4.6: Model Summary (Regression results)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R^2 Change	F Change	df1	df2	Sig.F Change	
Model 1	.737	.544	.537	1.84106	.544	84.042	34	2397	.000	
Model 2	.807	.651	.645	1.61329	.107	104.518	7	2390	.000	.957

gression model. The regression model is considered as a good fit if the adjusted R^2 is approximately equal to the R^2. Considering the values of both R^2 and Adjusted R^2, Model 2 was a better fit for the data collected during this experiment when compared to Model 1.

Change statistics

Change statistics explain the differences introduced by additional predictors to the regression model. Change statistics from Table 4.6 indicate that new predictors included in Model 2 made a significant (p <0.001) difference to the Model 1. The change statistics also indicate that Model 2 (with interaction variables), was a better fit of the data when compared to Model 1.

Model Parameters

Multiple linear regression can be represented in an equation form as shown below

$$Dependentvariable = b_0 + b_1(predictor_1) + b_2(predictor_2) + ... + b_i(predictor_i) \quad (4.1)$$

The dependent variable for both Model 1 and Model 2 was ‘duration’ to execute a segment and the predictors were the variables (except the ‘Constant’) listed against Model 1 and Model 2 in Table B (presented in Appendix I). The coefficients listed in the column B (unstandardised coefficients) correspond to the b_i values for corresponding predictor variable.

The greater the value of b_i, the greater is the influence of the predictor on the regression model. In Model 1 (excluding the constant, b_0 from Table B - Appendix I), Participants 3, 6 and 13 had the highest b_i values. Model parameters therefore indicated that Participants 3, 6 and 13 could have influenced the regression model.

The t-test statistics for the predictors (Participants 3, 6 and 13) listed under column 't' in Model 1 of Table B (presented in Appendix I) were high as well as significant. Therefore both the b_i values and t-test statistics suggest that these three participants were making significant contribution towards the regression model. This could introduce a potential bias based on strength of these contributions.

Model 3 and Model 4:

To avoid the potential bias, the data from these participants was excluded, and regression models 3 and 4 (similar to Model 1 and Model 2 respectively) were executed.

Figure 4.10 shows a comparison of model parameters obtained from all four regression models. The comparison of bars from unfiltered data (Model 1 and Model 2) with bars from filtered data (Model 3 and Model 4) respectively shows that the regression models did not depend on the influencing participants. Figure 4.10 also shows that the regression models with interaction variables clearly differed from the regression models without interaction variables. This was also evident from the change statistics presented earlier in this section.

Further analysis of interaction effects

Considering the b_i values of interaction variables from Model 2 that were significant (refer to the bottom rows of Table B (presented in Appendix I)), it was evident that segments with help from an embedded object and the reaching segments were influenced by the direction of movement with respect to gravity. Substituting these b_i values from Table B (presented in Appendix I) into equation 4.1, the durations for various combinations of conditions were

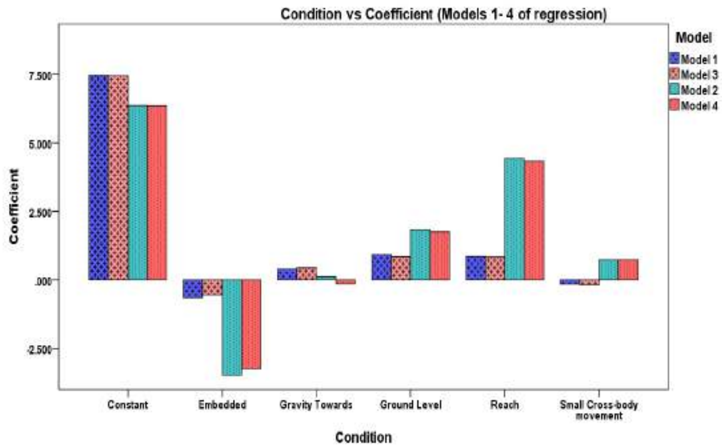


Figure 4.10: Condition vs. Coefficient (regression models 1-4)

Table 4.7: Condition Table (combination of input conditions chosen)

Condition I	Condition II	Condition III	Condition IV
Embedded (EV1)	-	Towards Gravity (G1)	-

calculated and presented in Table 4.8, a sample calculation with a particular combination of conditions (see Table 4.7) is shown below.

$$Duration = b_0 + b_{Embedded(EV1)} + b_{TowardsGravity(G1)} + b_{Embedded-TowardsGravity(EV1G1)}$$
$$= 6.358 + (-3.477) + 0.117 + 4.193 = 7.191s$$

Table 4.8: Duration(sec) calculated by substituting b_i values of interaction variables into equation 4.1

	Against Gravity (G0)	Towards Gravity (G1)	Ground level (G2)
Virtual (EV0)	6.358	6.475	8.190
Embedded (EV1)	2.881	7.191	7.543
Return (RR0)	6.358	6.475	8.190
Reach (RR1)	10.792	8.227	8.864

The difference in execution times of the embedded and the virtual segments (Table 4.8), was greater when the movement was against gravity. In the other two cases (towards gravity and ground level) there existed a difference in the execution times of the virtual and the embedded segments, but the magnitude of the difference was small. In case of reaching/returning segments, the reaching segments in general required longer execution times when compared to the returning segments, but the magnitude by which the execution times were longer depended on the direction of the movement with respect to gravity. There was also a mild interaction between the reaching and the cross-body movement involved in executing the segment. The reaching segments with a large cross-body movement required slightly longer execution times when compared to the reaching segments with small cross-body movement. This difference was very small in case of the returning segments.

4.5 Discussion

The primary aim of this study was to test the adaptability of the GENTLE/A system, to the duration to execute point-to-point movements, according to the performance of the participant. The next aim was to study the influence of various conditions imposed during point-to-point movements on the performance of the participant.

The results from iteration level analysis showed that the algorithm could successfully tune the duration to the participant optimum constant value for point-to-point movements. Segment level analysis identified varying number of participants reaching a constant optimum value of duration during different segments. Furthermore it was observed that the default duration set at the beginning of the AA2 mode repetitions almost always scaled down during all the segments for all the participants by the end of the five repetitions. The differences in the performance identified at the iteration level and segment level inform that the number of repetitions required to reach a constant optimum value of duration for various segments needs to be personalised.

Investigations into underlying reasons for the varying patterns of duration adaptation for different segments led to the study of the influence of the conditions imposed during different segments. Regression was chosen to carry out these investigations and among the four regression models, the models which included interaction variables (variables representing the interaction effects between various conditions) showed a better fit of data with greater R^2 values.

Embedded vs. Virtual

The results from the regression showed that segments with the target point represented by an embedded object required a shorter time for execution when compared to segments with the target point just displayed in the virtual environment. This result was consistent with a related study carried out by the colleagues in our research group (Bowler et al., 2011) and with an article reporting recent trends in robot-assisted therapy environments (Johnson, 2006). The improved performance of healthy participants in the presence of a real-world object when compared to a virtual object clearly indicated that the virtual worlds are relatively more difficult even for participants with good cognitive abilities. Considering the stroke patients with impaired cognitive abilities, it is thought that an embedded set-up would be cognitively less demanding when compared to a complete virtual environment and might encourage and assist the participant in performing better during a therapy session.

The positioning of the real targets did not exactly match with the virtual targets on the screen (refer to section 4.3.1 for rationale underlying the design of the embedded set-up). In spite of this mismatch, the regression model that included various other possible conditions that could have influenced the movement duration still showed that the embedded segments were quicker to execute when compared to virtual segments. Future studies with distinct set-ups with only virtual targets and only real targets would facilitate evaluation of the performance differences based on various presentations of the targets.

Reach vs. Return

In our previous studies with the GENTLE/A rehabilitation system, a fixed constant duration was given to execute any segment and the reaching segments were always against gravity and the returning segments were always towards gravity. Results from a previous study demonstrated that participants failed to lead the robot most of the times during the returning segments when compared to the reaching segments (see Section 3.5). The regression results from the current study showed that segments involving a reaching movement required longer execution time when compared to a returning movement irrespective of the gravity. It is understood from the results from this study that the major factor influencing the leading behaviour during reaching/returning movements was not the gravity but the duration required to execute different types of movements. One possible explanation for the difference in execution times could be the varying muscle groups involved to execute the reaching and the returning movements. This involves studying the kinematics of upper arm movements which forms part of our future work.

Movement direction with respect to Gravity

When compared to embedded vs. virtual and reach vs. return, the different directions of gravity had a smaller influence on the duration to execute a point-to-point movement. Unexpectedly, the final durations after the five iterations of the AA2 mode for ground level segments were slightly longer when compared to segments with direction of movement either against or towards gravity. Also the number of participants reaching a constant optimum value within five iterations for the ground level segments was relatively lower when compared to other segments with larger influence of gravity. The segments that were executed at ground level were smaller in length when compared to other segments. The segments which are shorter in length would require less time for execution and hence the algorithm used for adapting the duration requires larger number of iterations to reach a constant optimum value, given that all segments start at same set duration. This point needs further consideration in improving our adaptation algorithm.

Interaction effects

The conditions imposed during various segments not only influenced independently but also had interaction effects on the performance of the participant. These interaction effects were evident in Model 2 and Model 4. Segments with help from the embedded object were quicker to execute when compared to the virtual segments. This difference in execution times between segments with the embedded and the virtual targets was largest when moving against gravity when compared to moving towards gravity or ground level movements. Similarly durations for the reaching segments when compared to the returning segments were longer when working against gravity and shorter when working towards gravity or at ground level. The cross-body movement had a slightly greater impact on the reaching segments when compared to the returning segments. The influence of these interaction effects on the performance of the participant requires further investigation.

The study was conducted with healthy participants and no arm weight support against gravity was provided. Therefore the influence of gravity on muscle synergies involved in various movement patterns could be responsible for the interaction effects observed, which needs further investigations.

Adaptability approach

The haptic assistance/resistance offered by the HapticMaster was realised by rendering a spring-damper combination at the HM's end-effector. The spring-damper combination acts as an elastic band gently pulling the user's arm to match the MJT position at the given point in time. This arrangement offers assistance when the user is lagging, but it transforms into resistance when the user is leading and trying to reach the target quicker than the MJT. The former response (assistance while lagging) could be motivating in clinical settings when the user is in the early stages of recovery. But as the recovery progresses and the user consistently leads the activity, the response of the system becomes 'isoresistive'. Isoresistive training with a continuously scaling challenge is thought to be useful with healthy users. But in the rehabilitation scenario altering the challenge to suit the user's performance is thought to be a more suitable adaptability strategy.

4.6 Chapter summary

The study presented in this chapter could successfully evaluate the adaptive nature of the GENTLE/A rehabilitation system with healthy participants. The system could successfully adapt to the *leading/lagging* performances of the participants, as informed by the Δ*Effort* parameter and alter the duration required to execute point-to-point movements. Whether the adaptability of the GENTLE/A system would be of greater use in clinical settings, where a large variability is expected in the performance of the patients, is subject of our future research. However, this study shows that different patterns of arm movement, as well as different presentation for targets, can influence the durations set to achieve targets. This is an important consideration for studies applying a set duration to achieve reaching and returning trajectories. The constant optimum value of duration to which the system adjusts could also be used as an assessment parameter across the block of interaction sessions in clinical settings.

The results from the study also showed that participants were quicker in executing point-to-point movements in the embedded set-up when compared to the virtual environment. This indicated that the embedded targets were better perceived when compared to the virtual targets shown on the monitor. The difference may be comparable or more pronounced in the case of stroke patients with comparatively lower cognitive abilities, so the use of the embedded and the real objects could be potentially less cognitively challenging for stroke patients. The reaching movements required longer execution times when compared to the returning movements irrespective of the influence of the gravity. Further investigations into the kinematics of the upper arm involved in the reaching and the returning movements might shed further light on the differences observed.

Chapter 5

Adaptive algorithm II

5.1 Introduction

The process of rehabilitation is to relearn the 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 progresses. Adaptive algorithm I auto-tuned the task according to the user's requirement, this strategy would be more suitable for earlier stages of training in order to motivate the user to train more. In order to address the second requirement to challenge the user when the user starts to actively contribute (lead) while executing a task, we proposed a complementary adaptability strategy. Once the Δ*Effort* parameter identifies that the user is leading the interaction, the challenge in the task could be altered based on the extent of lead indicated by the Δ*Effort* parameter. Using this parameter and its derivations (presented in section 5.3.1), we proposed a performance based training algorithm (adaptive algorithm II). This algorithm would adapt the task difficulty based on the performance of the user interacting with the GENTLE/A system.

The adaptive algorithm II was successfully evaluated with healthy users in a pilot study

(PS-III) with eleven participants. Exp-III targeted to test the findings from PS-III with greater number of participants and also aimed to learn more about the adaptability of the system when the users execute similar tasks using the two algorithms. Exp-III was designed to study how the task difficulty levels change when the task is not tuned according to user's requirement and how the difficulty levels would change when the task is tuned to user's requirement. This essentially means executing a task using the adaptive algorithm II, then the adaptive algorithm I and followed by the adaptive algorithm II in that order. The experimental protocol for Exp-III was outlined accordingly (see Figure 5.4). The results from PS-III and Exp-III are presented in this chapter.

5.2 Research Questions

RQ3: How can the performance indicators be used to improve the adaptability of the GENTLE/A rehabilitation system?

A system auto-tuning to user's requirement could be compared with the therapist(s) offering more assistance in the early stages when the patient is more compromised. Adaptive algorithm I implemented a similar strategy by auto-tuning the duration given to execute point-to-point movements based on the lead-lag role informed by the Δ*Effort* parameter.

In rehabilitation settings as the recovery progresses a therapist would alter the strategy and make the task challenging. The therapist would also scale the challenge up or down based on the performance of the patient. Therefore adaptive algorithm II was designed to identify the extent of lead achieved by the user based on the Δ*Effort* and parameters derived from the Δ*Effort*. The algorithm then adapts the challenge in the task based on the extent of lead identified (*RQ3*).

5.3 Experiment

5.3.1 Terminology and parameters

During the execution of any segment (point-to-point movement), data was sampled at 50 ms time intervals. The Cartesian coordinates were recorded at every sampling interval and various parameters were calculated to indicate the performance and contributions of the user (see Fig. 5.1 for a pictorial representation). The new parameters, in addition to the parameters used in our previous studies, that were introduced are presented below:

%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.

Active mode (α): The first three iterations of the active mode performed before the active-assisted mode in Exp-III (see Figure 5.4c) were named as active mode (α).

Active mode (β): The last three iterations of the active mode performed after the active-assisted mode in Exp-III (see Figure 5.4c) were named as active mode (β).

5.3.2 Experimental set-up

The experimental set-up for PS-III and Exp-III remained the same as Exp-II (see section 4.3.1) but for modifications in the embedded environment and implementation of the

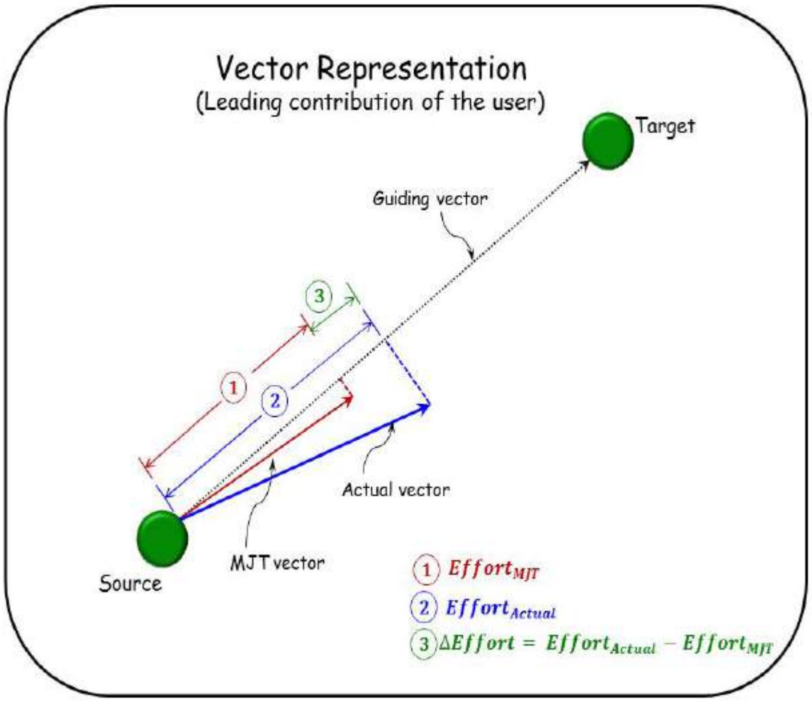


Figure 5.1: Vector representation

adaptive algorithm II.

5.3.2.1 Adaptive algorithm II

The parameter *ΔEffort* could successfully indicate the leading-lagging status of the user in our earlier studies with the GENTLE/A system. Utilising the *%Contribution*, derived from *ΔEffort*, as a performance indicator we proposed an adaptive algorithm that would autonomously alter the task difficulty. The algorithm was 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))* (Amirabdollahian et al., 2001), that allows the movement to progress towards the target only when the user actively contributes and leads the activity.

$$E(t) = (p(t)\text{-}p'(t))^2$$

where *p'(t)* is the actual position of the robot and *p(t)* is the position the robot has to achieve according to the reference trajectory (MJT) at the time t. Thus for any 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 (Cameirão et al., 2010). The algorithm is presented as a flow-chart (Fig. 5.2). 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 the 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*.

5.3.2.2 Embedded set-up

The results from Exp-II showed an improved performance from the users in the presence of a real object alongside the virtual object. During Exp-II not all target points that were

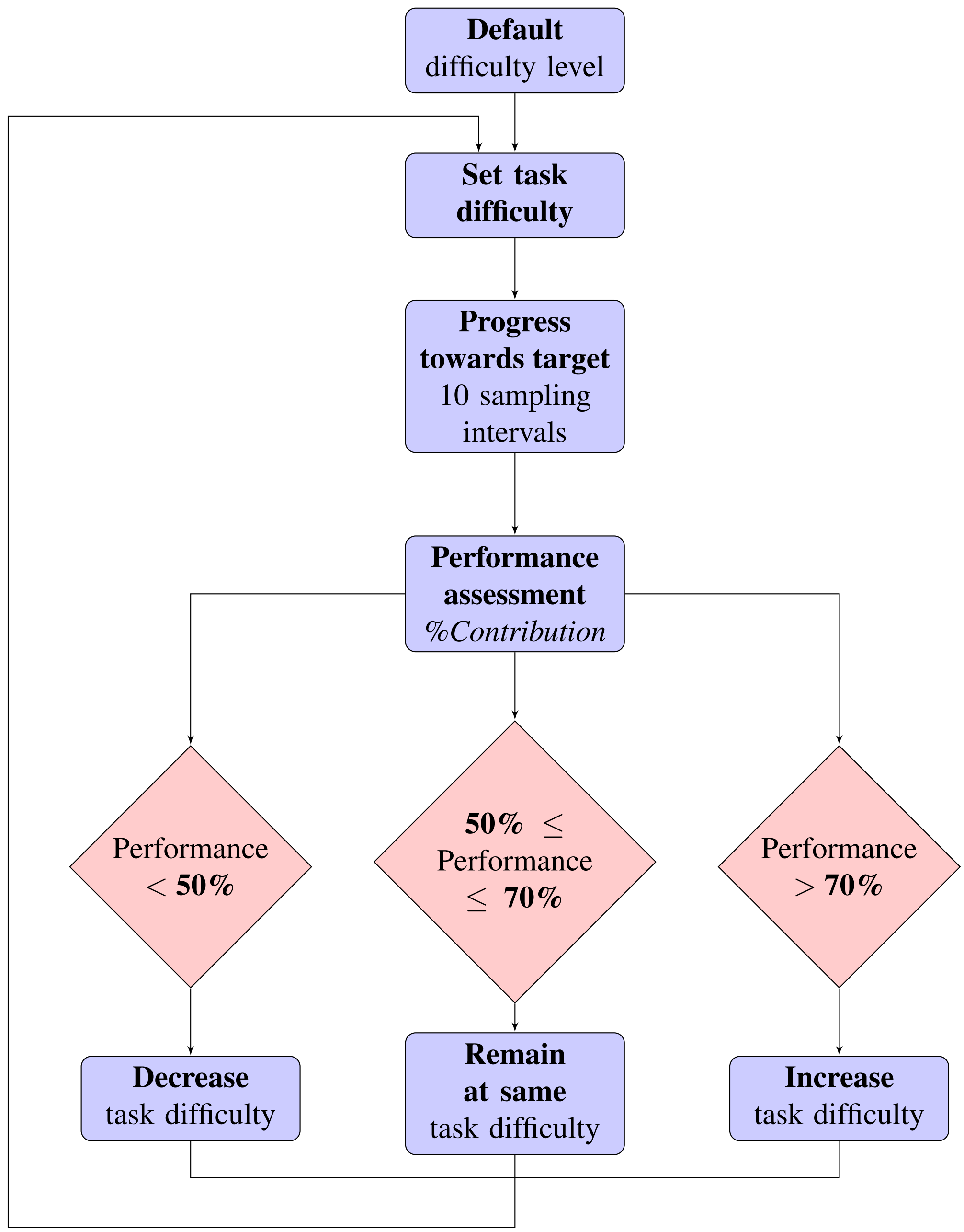


Figure 5.2: Flow-chart representation of Performance based training algorithm

used during the experiment had both virtual and real objects. In addition the real objects were either embedded as ping-pong balls or stickers, based on the position of the target point in the workspace and its interference with the movement. In order to make the target presentation uniform and investigate the advantages of embedded vs virtual objects, the embedded set-up is modified in Exp-III (Figure 5.3). The real objects were included as numbered stickers where number represented the sequence in which the points are visited during a mode. A sub-set of points from the set used in Exp-II was chosen for these studies. The segments executed at ground level in Exp-II were excluded and pairs of segments with reach-return and towards-against gravity were included during these studies, which left us with a set of eight points (see numbered stickers from 1-8 in Figure 5.3).

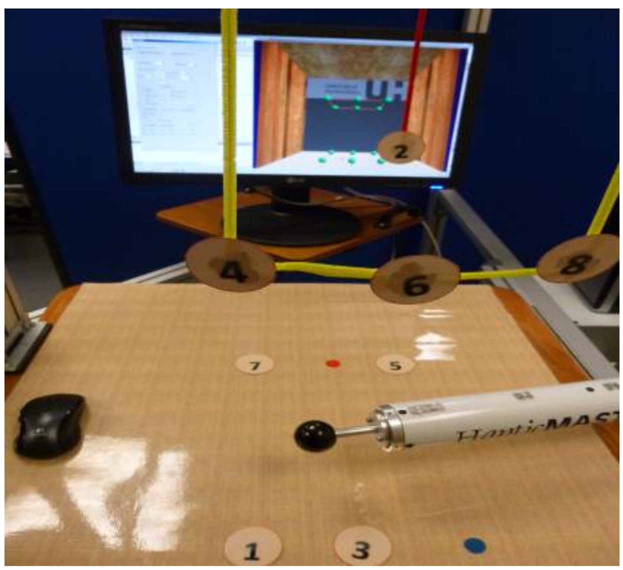


Figure 5.3: Embedded environment

5.3.3 Participants

The pilot study (PS-III) included eleven healthy participants (2 female and 9 male), age ranging 26.9 $\pm$ 6.6 (mean $\pm$ standard deviation) and Exp-III included 40 healthy participants (18 female and 22 male), age ranging 32.9 $\pm$ 10.2. Written informed consent was obtained from each participant before inclusion in the studies and ethical approval of the evaluation protocol was obtained from the University's ethics committee (under University of Hertfordshire approval number 1213/28).

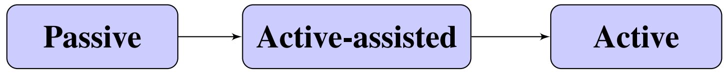
5.3.4 Experimental protocol

We followed the same structure of 'Training' phase followed by 'Actual-performance' phase as in our previous studies. During the training phase, participants were briefed about all the three modes (passive, active-assisted, active) 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 addition to the data recorded by the system, we obtained feedback from the participants in the form of questionnaires. The aim of questionnaire feedback was to evaluate the performance of the system from the viewpoint of the participant. The questionnaires used during both PS-III and Exp-III are presented in Appendix II. Figure 5.4 illustrates the experimental protocol during PS-III and Exp-III.

PS-III: The actual-performance phase involved executing active mode for five iterations. During these iterations the system autonomously tuned the difficulty of the task according to the adaptive algorithm II (presented in later section). Towards the end of the fifth iteration the participant was given a small questionnaire to complete.

Exp-III: The actual-performance phase involved executing active mode (3 iterations), AA2 mode (5 iterations) and active mode (3 iterations) in succession. At the end of the second set of active mode iterations the participant was given questionnaire to complete.



(a) Training (PS-III & Exp-III)

(b) Actual-performance (PS-III)

(c) Actual-performance (Exp-III)

Figure 5.4: Experimental protocol (PS-III & Exp-III)

5.4 Pilot Study III

5.4.1 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 task difficulty level 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.

Every segment was executed five times by each participant during the five repetitions of the 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

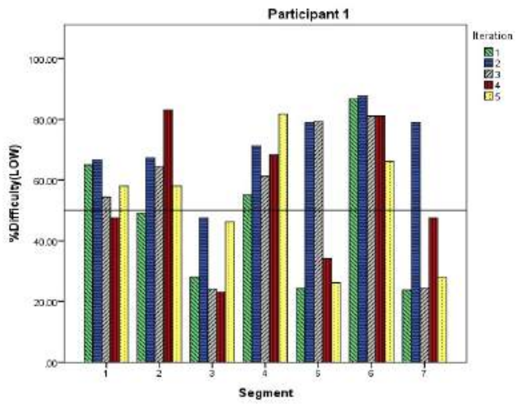


Figure 5.5: Performance of Participant 1

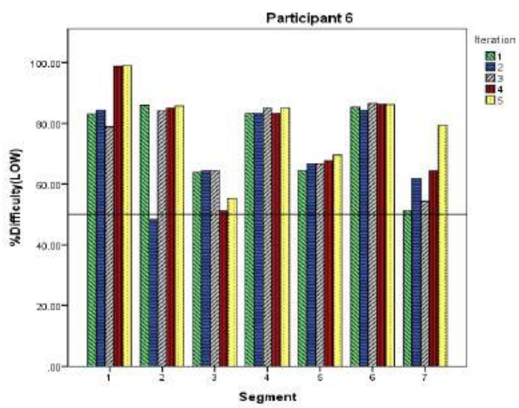


Figure 5.6: Performance of Participant 6

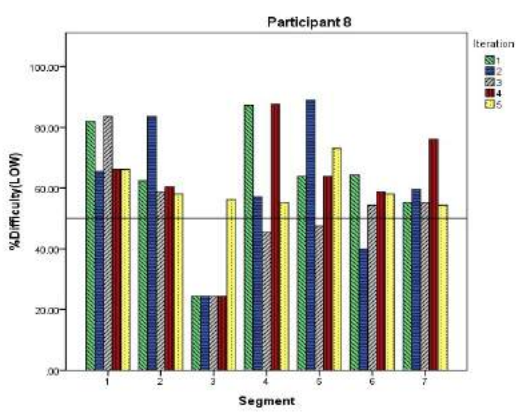


Figure 5.7: Performance of Participant 8

Table 5.1: Performance evaluation rules (PS-III)

%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

the number of sampling intervals at high task difficulty level (high spring stiffness) for that segment. Fig. 5.5 - Fig. 5.7 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.

We used simple rules presented in Table 5.1 to study these plots. Applying these rules to segment-5 of Fig. 5.5, 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. 5.6 and Fig. 5.7 respectively. The performance of the system as projected by the data recorded by the HM is highlighted through these plots.

The next stage 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 5.2. When the participants were asked to rate the challenge in the task, 5/11 participants rated the challenge 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

Table 5.2: Questionnaire summary (PS-III)

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

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.

Hypothesis: Our underlying hypothesis while carrying out this examination was, if the performance of a participant is spread between high and low task difficulty levels during the entire experimental session, this would prompt the participant to perceive the difference in task execution (i.e., perceive the difference in the 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 being very little would go unnoticed by the participant.

In order to estimate the performance of the participant across all the five iterations of the active mode we calculated the sum of *%Difficulty(LOW)* across the five iterations of each segment and extended the rules presented in Table 5.1 to '> (5x50)' and '<= (5x50)' for low and high task difficulty levels respectively. Fig. 5.8 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 'any difference perceived in the task execution'. 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, 8 and 11 the performance was spread between high and low task difficulty levels (see Fig. 5.8 above and below *%Difficulty(LOW)* =250) and they perceived a difference in executing the task (questionnaire response 'Yes') and this was in agreement with our hypothesis. Similarly, for participants 4, 6, 9 and 10 the performance was confined to low task difficulty level (see Fig. 5.8 above *%Difficulty(LOW)* =250) and the participants could not perceive a difference in the task execution (questionnaire response 'No') and this was also according to our hypothesis. But the performance and questionnaire responses of participants 5, 7 and 2 were not according to our hypothesis. In summary, for 8/11 participants the system's response and the participant's observation matched.

Our previous study (Exp-II) with GENTLE/A system 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. The feedback received for 'usefulness of the embedded object' through the questionnaire supports previous findings (section 4.5, Bowler et al., 2011; Johnson, 2006). 5/11 participants responded with 'Very useful' for the embedded environment,

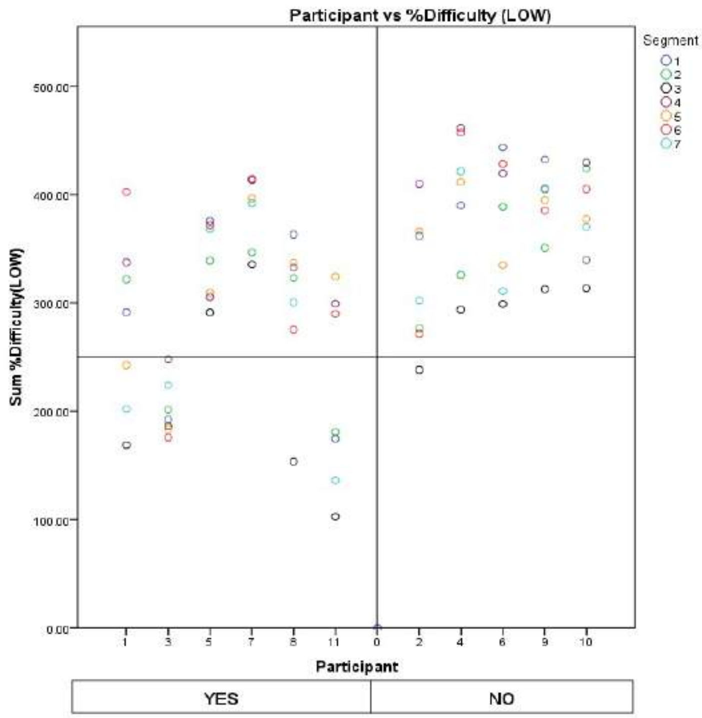


Figure 5.8: Performance summary plot of all the participants

4/11 with 'somewhat useful' and 1/11 was 'neutral'.

5.4.2 Findings (PS-III)

This pilot study could successfully evaluate the performance of the adaptive algorithm-II implemented on the GENTLE/A system. Comparing questionnaire responses with the system recorded performance parameters, a greater share (8/11) of responses received through the questionnaire also confirmed the difference in the task difficulty level as perceived by the participants. The embedded environment was rated as very useful by the majority of the participants.

Although we highlighted our hypothesis, that a spread 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 2. A potential explanation for this observed difference could be that high and low task difficulty levels in our data analysis followed an assignment of spring stiffness values to low and high categories. An individual's perception of task difficulty may not necessarily relate to such assignment. However, we maintain that performance indicators like *%Difficulty(LOW)/(HIGH)* can provide a good insight into dynamic change of difficulty during different HRI sessions.

5.5 Experiment III

5.5.1 Results and Analysis

The data recorded during the two sets of the active mode (α and β), where adaptive algorithm-II was put to test, was analysed and results presented in this section. The AA2 mode that was executed between active mode (α) and active mode (β) tuned the duration given to execute point-to-point movements according to the adaptive algorithm I. The experimental protocol for the AA2 mode iterations remained the same as in Exp-II and hence the data recorded during the AA2 mode repetitions was not analysed as the performance evaluation of the adaptive algorithm I was already presented in detail in Chapter 4. The raw data from the iterations of the active mode was organised as shown in the Figure 5.9

The rest of this section is organised to present the hypothesis and results from the statistical tests conducted at each level (following a top-down approach) of the data organisation presented in Figure 5.9.

5.5.1.1 Participant level analysis

Hypothesis-1: As the participants were asked to perform at their natural pace and comfort during the active mode, it was expected that the performances of the participants (in general) differed significantly.

The adaptive algorithm-II was designed to tune the system's response based on the

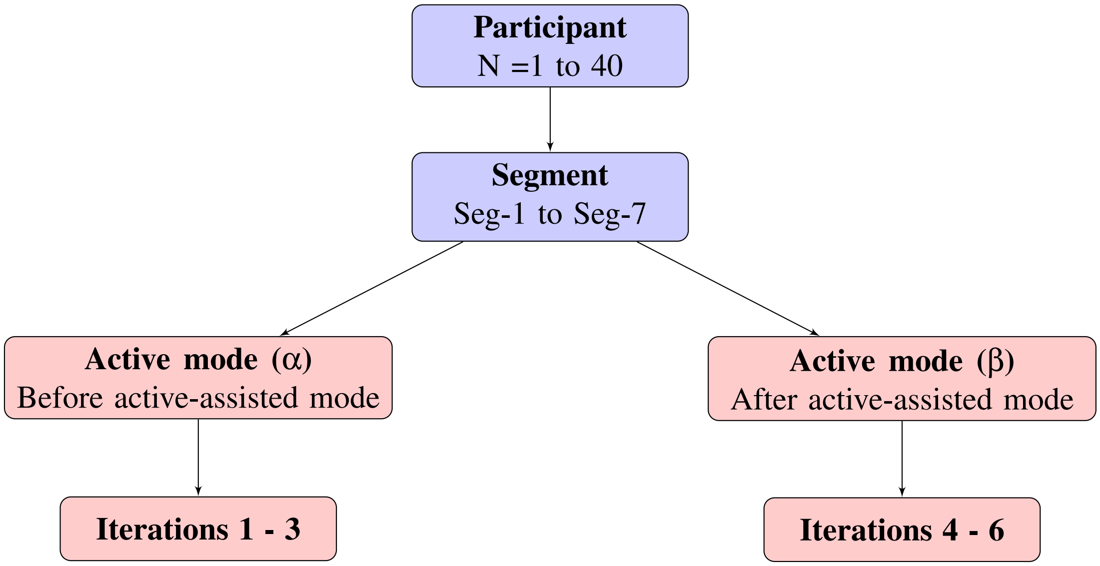


Figure 5.9: Raw-data organisation for Exp-III

performance of the user. Hence it was expected that the parameters like *%Difficulty(LOW)* indicating the performance of the user differ significantly at the participant level. We carried out a Oneway ANOVA (Table 5.3) with *%Difficulty(LOW)* as dependent parameter and participant as a factor. The results showed that the performance as informed by the *%Difficulty(LOW)* parameter was significantly different (p=.000) at the participant level which agrees with the hypothesis-1. Figure 5.10 also illustrates varying performance of participants as informed by *%Difficulty(LOW)* during Exp-III.

Along with Oneway ANOVA, post hoc tests (Tukey's test) were performed to study the influence of various participants who took part in the study. The idea behind these further tests was to ensure if any of the participants were differing significantly in their performance from the rest of the participants in the study. This might indicate that the participants were either highly influencing the results or did not clearly understand the task at hand. The detailed results from Tukey's test are presented in Table C (listed in Appendix I [d]). Figure 5.11 shows a summary plot of Tukey's test results. The figures on

[d]Provided in a CD that accompanies the thesis, as statistical information at this level might only interest a small group of readers

Table 5.3: Oneway ANOVA (Participant, *%Difficulty(LOW)*) (Exp-III)

			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		80881.767	39	2073.891	13.318	.000
	Linear Term	Contrast	15313.618	1	15313.618	98.342	.000
		Deviation	65568.149	38	1725.478	11.081	.000
Within Groups			255377.231	1640	155.718		
Total			336258.998	1679			

y-axis of the plot show a count of the number of participants whose performance means significantly differed from the participant on x-axis, for e.g., the performance mean for Participant 2, as indicated by *%Difficulty(LOW)*, significantly differed from performance means of 22 other participants who took part in the study. The bars coloured in 'red' are the participants whose performance is significantly different from majority (>20 out of 40) of the participants in the study. Therefore from Figure 5.11 it can be inferred that Participants 2, 5, 6, 16 and 33 could have influenced the results of the Oneway ANOVA test. We conducted Oneway ANOVA excluding these participants, but the results obtained still showed that the performance as informed by *%Difficulty(LOW)* significantly differed at the participant level which is again in agreement with hypothesis-1.

5.5.1.2 Segment level analysis

Hypothesis-2: The segments executed during Exp-III differed in the various input conditions (detailed below) and hence the performance of the participants at segment level was expected to differ significantly.

The seven segments executed by the participants during Exp-III (see Figure 5.12 and Table 5.4) differed in the length, the movement type involved like reach-return, away-

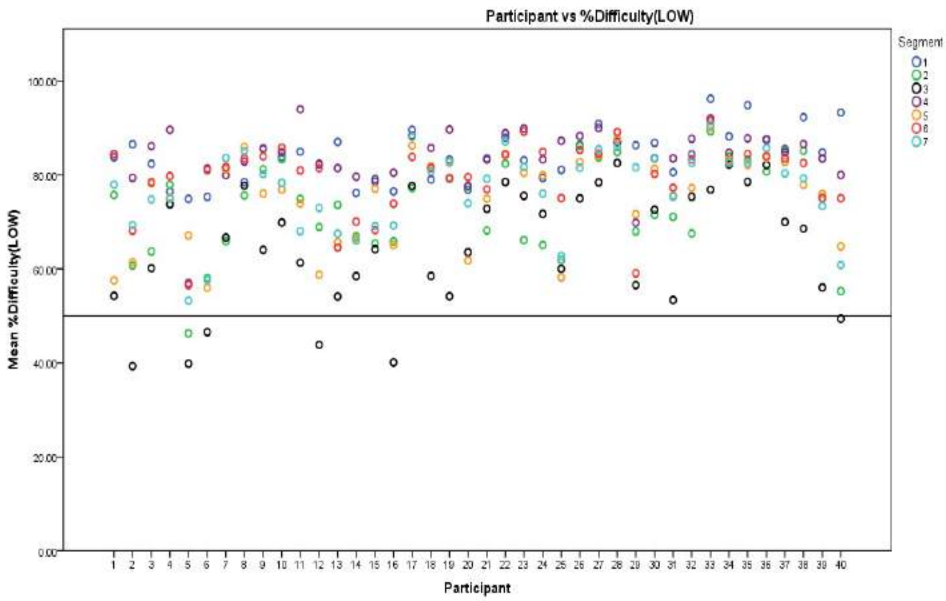


Figure 5.10: Performance summary plot for all the participants during Exp-III

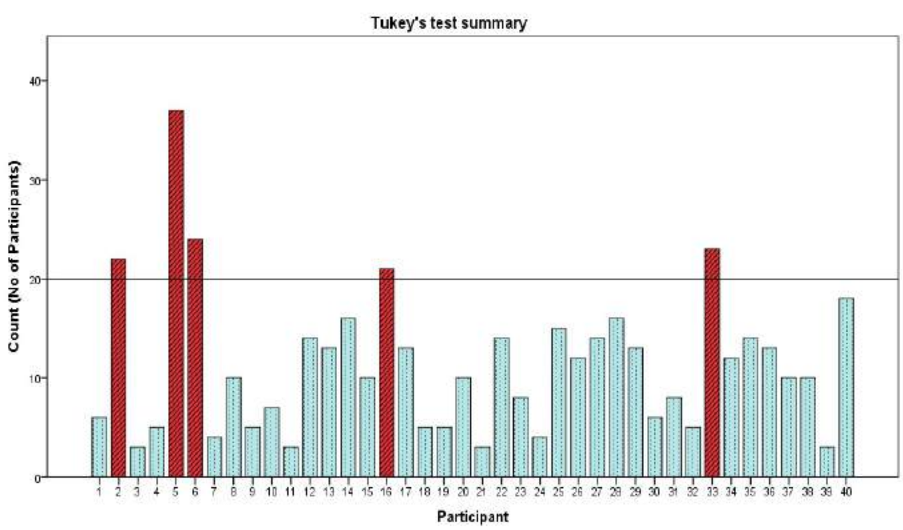


Figure 5.11: Tukey's test Summary for Oneway ANOVA (Participant, *%Difficulty(LOW)*)

towards gravity, large-small cross-body component and the movement direction (left side to right side of the body or vice-versa). The results from Oneway ANOVA with *%Difficulty(LOW)* as dependent parameter and segment as a factor are presented in Table 5.5. The results showed that the performance of the participants was significantly different (p=.000) at the segment level which is in agreement with the hypothesis-2.

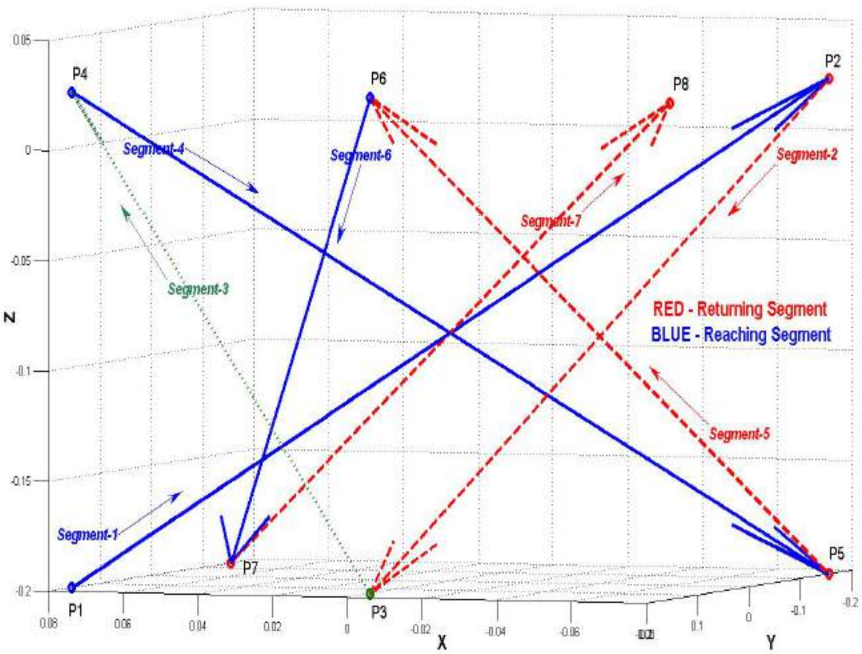


Figure 5.12: Segments executed by participants in Exp-III

Similar to the participant level analysis, post hoc tests were conducted to study if there existed any inherent differences and similarities in performance of the participants during various segments. The detailed results from the Tukey's post hoc test are presented in Table D (listed in Appendix I [e]). The segments during which the performance was not significantly different according to the Tukey's test are plotted in Figure 5.13. It can be observed that there are no data points for Segment-3 in Figure 5.13, which informs that the performance of the participants during Segment-3 significantly differed from their performance during all the other segments. Segment details presented in Table 5.4 and Figure 5.12 also show that Segment-3 was the shortest of all the segments and also different from the rest of the segments in terms of movement conditions involved.

[e]Provided in a CD that accompanies the thesis, as statistical information at this level might only interest a small group of readers

Table 5.4: Segment Details - listing input conditions and length of the segment (Exp-III)

Segment	**Length (m)**	**Reach-Return**	**Against-Towards gravity**	**Large-Small Cross-body component**	**Left(L)→Right(R) or Right(R)→Left(L)**
Seg-1	0.42	Reach	Against	Large	L → R
Seg-2	0.39	Return	Towards	Small	R → L
Seg-3	0.24	-	Against	Small	R → L
Seg-4	0.42	Reach	Towards	Large	L → R
Seg-5	0.39	Return	Against	Small	R → L
Seg-6	0.39	Reach	Towards	Small	R → L
Seg-7	0.42	Return	Against	Large	L → R

Table 5.5: Oneway ANOVA (Segment, *%Difficulty(LOW)*) (Exp-III)

			Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	(Combined)		65705.524	6	10950.921	67.716	.000
	Linear Term	Contrast	7.012	1	7.012	.043	.835
		Deviation	65698.512	5	13139.702	81.251	.000
Within Groups			270553.474	1673	161.718		
Total			336258.998	1679			

The performance plot (Figure 5.13) also shows that the performance of the participants was not significantly different during Segment-1 and Segment-4. Segment details (see Table 5.4) show that Segment-1 and Segment-4 are similar in all respects, except for movement against/towards gravity. Similar inference also applies to Segment-2 and Segment-5. The similarities identified between Segment-5 and Segment-7 pair and Segment-6 and Segment-7 pair by the performance plot (Figure 5.13) were not consistent with the segment details.

In summary segment level analysis shows that *%Difficulty(LOW)* could explain the performance differences based on the input conditions of the segments executed by the participants in some of the cases, though it failed to explain in few other cases.

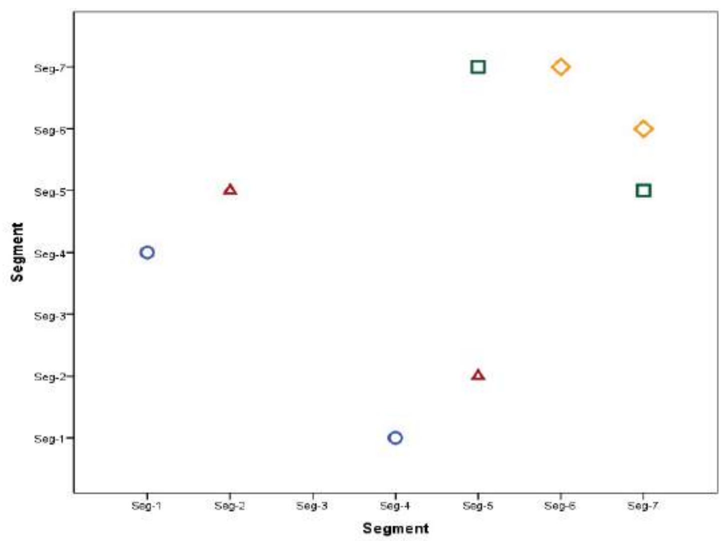


Figure 5.13: Segments with no significant difference in performance
Tukey's test Summary for Oneway ANOVA (Segment, *%Difficulty(LOW)*)

5.5.1.3 Analysis based on type of Active mode (α / β)

Hypothesis-3: The performance during the *active mode* (α)), that was executed before the system was tuned according to the adaptive algorithm-I, differs from the performance during the *active mode* (β), that was executed after the system tuning.

Table 5.6: Oneway ANOVA (Active mode type(α/β), *%Difficulty(LOW)*) (Exp-III)

		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	(Combined)	392.183	1	392.183	1.959	.162
	Linear Contrast Term	392.183	1	392.183	1.959	.162
Within Groups		335866.816	1678	200.159		
Total		336258.998	1679			

The results from the Oneway ANOVA with *%Difficulty(LOW)* as dependent parameter and Active mode type (α/β) as factor are presented in Table 5.6. Oneway ANOVA shows the performance of the participants during active mode (α) and active mode (β) was not significantly different (p=0.162), this is in disagreement with our hypothesis-3.

In order to study if the Oneway ANOVA results were influenced by some of the participants, we excluded the participants 2, 5, 6, 16 and 33 identified by *participant level analysis* as strong influencers and conducted the Oneway ANOVA again. The results from the second test of Oneway ANOVA (Table 5.7) with filtered data show that the performance during active mode (α) and active mode (β) was significantly different (p=0.023). The box plot (Figure 5.14) also shows a difference in *%Difficulty(LOW)* from active mode (α) to active mode (β). Though the medians for both sets are nearly the same, the lower quartile of active mode (β) is lower than active mode (α) and active mode (α) has many outliers.

5.5.1.4 Regression

Regression was conducted to study the influence of participants, segments and active mode type (α/β) as input(dummy) variables on the outcome variable *%Difficulty(LOW)*. The

Table 5.7: Oneway ANOVA (Active mode type(α/β), *%Difficulty(LOW)*)
Data from Participants 2, 5, 6, 16 and 33 excluded (Exp-III)

			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		840.426	1	840.426	5.214	.023
	Linear Term	Contrast	840.426	1	840.426	5.214	.023
Within Groups			236614.700	1468	161.182		
Total			237455.126	1469			

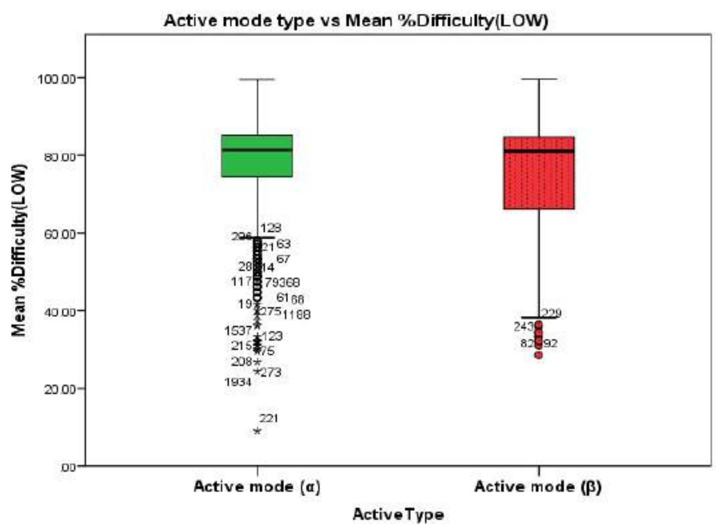


Figure 5.14: Means plot (Active mode type vs Mean of *%Difficulty(LOW)*)

data from participants 2, 5, 6, 16 and 33 was excluded in the regression model. The regression model summary is presented in Table 5.8 and the coefficients of the regression model are presented in Table 5.9. The R Square value (=.013) is very small and hence not much variability in the outcome variable (*%Difficulty(LOW)*) was explained by the input variables included in the regression model. But the table (Coefficients) shows that the coefficient for 'active mode type' (=-1.512) was significantly (p=0.022) influencing the

Table 5.8: Model Summary (Regression results)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Model 1	.112	.013	.011	12.64619

Table 5.9: Coefficients of regression model

Model		Unstandardised Coefficients		Standardised Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	77.638	1.392		55.783	.000
	Participant	.109	.030	.095	3.667	.000
	Segment	.046	.165	.007	.281	.779
	Active Type(α/β)	-1.512	.660	-.059	-2.292	.022

outcome variable though by a small amount.

While interpreting these regression results one must also be aware that various input conditions (reach-return, against-towards gravity, etc.) that were proven to be having effect on the performance of the participants were not included in this regression model. This could be the reason for a very low R Square value in this regression model. As the aim of the analysis was to evaluate the adaptive algorithm-II during the active mode (α/β), the input parameters were restricted to the new parameters used in Exp-III.

The regression results outline that 'active mode type' did influence the performance of the participants as informed by *%Difficulty(LOW)* though the effect was very small.

5.5.1.5 Questionnaire responses

The questionnaire used to collect responses at the end of Exp-III is presented in the Appendix II. The first question was the 'toughest point to reach', the responses are shown in Figure 5.15. The responses were presented in terms of 'segments' (instead of 'points'), as it would be easier to relate with the structure of analysis presented in this chapter. The plot illustrates that Segment-3 was perceived as the toughest segment by many participants. Segments 2, 4 and 6 were perceived as toughest segments by very low number of participants. The response for toughest segment as Segment-1 may not be a true representation as there was an extra audio cue at the beginning of Segment-1 which many participants found it confusing. Figure 5.16 presents the iteration-wise performance of the participants as a mean of *%Difficulty(LOW)* during various segments. The line for Segment-3 is a the lower end of the plot 5.16, indicating that the participants executed a relatively smaller part of Segment-3 at lower task difficulty level. This could be the reason for the participants perceiving Segment-3 as the toughest segment in the questionnaire. Similarly it can be inferred from the plot that the participants executed major parts of Segments 4 and 6 at lower task difficulty levels. This also supports very low number of participants finding Segments 4 and 6 to be tougher to execute in the feedback through questionnaire. The questionnaire responses for Segments 2, 5, and 7 (Segment-1 was excluded because of confusing audio), were not consistent with the performance informed by *%Difficulty(LOW)*.

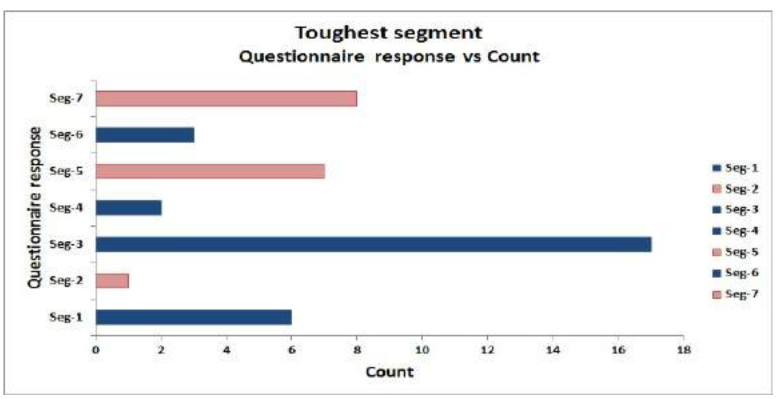


Figure 5.15: Questionnaire responses for 'toughest point to reach'

The response for usefulness of the embedded object from the questionnaire is presented in Figure 5.17. The responses are similar to the responses from PS-III and in favour of the presence of the real target object alongside the virtual target object. The next

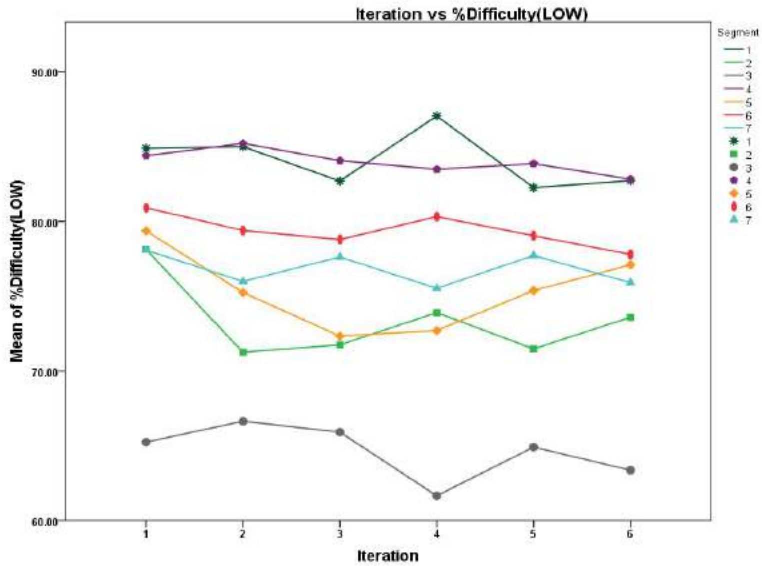


Figure 5.16: System recorded data (Iteration vs Mean of *%Difficulty(LOW)*

two questions were related to the active mode type (α/β). The first question was if the participant perceived any difference while executing the first set of the active mode repetitions (α) and the last set of the active mode repetitions (β) and the participants responded with 'YES/NO'. If the responses was 'YES' the participants were asked to briefly explain the difference perceived in the next question and this question was interpreted to explore which of the active modes (α or β) was felt to be difficult to execute by the participant. Figure 5.18 shows that 14/40 participants responded with 'YES' and 26/40 participants responded with a 'NO/NOT SURE' for difference perceived between active mode (α) and active mode (β).

The experimental protocol for Exp-III involved a set of repetitions of the AA2 mode between the first and the last sets of the active mode repetitions. Many participants expressed that due to a reasonably big time gap between the two sets of active mode repetitions, they couldn't clearly remember their perception during the first set of active mode repetitions. This could be a major contributor for a greater number (26/40) of 'NO/ NOT SURE' responses in the questionnaire feedback. Out of the fourteen participants who responded with an 'YES', ten participants felt that the last set of repetitions (β) was easier to execute and four participants felt that the last set of repetitions were tougher when compared to the first set (α). In the current state of the design of the adaptive algorithms (I and II) we were expecting a difference to be perceived between the two sets of active modes executed, but one set being perceived tougher/easier when compared to the other set depends upon the way the duration was tuned during the AA2 mode repetitions. This could form a point to be explored as part of future work.

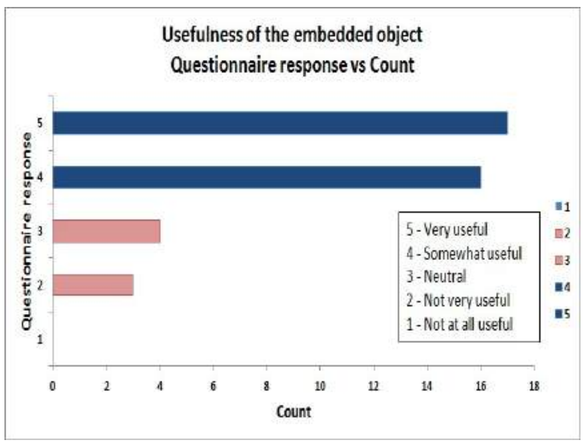


Figure 5.17: Questionnaire responses for 'usefulness of the embedded object'

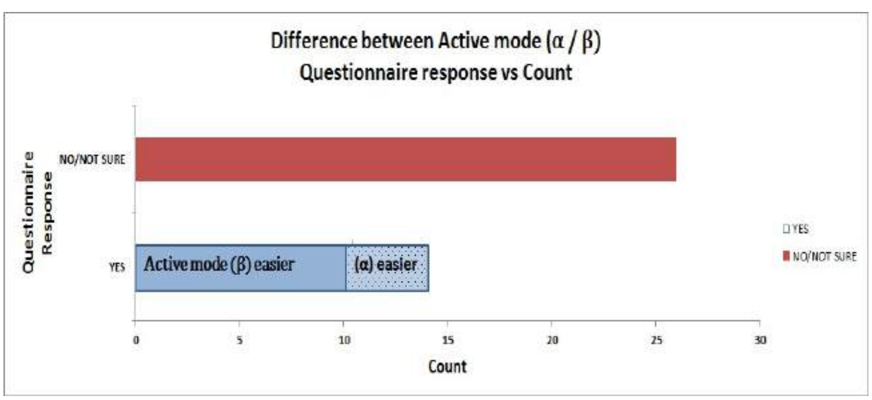


Figure 5.18: Questionnaire responses for 'difference between first 3 (α) and last 3 (β) repetitions of the active mode'

5.6 Discussion

The results from the pilot study showed that the adaptive algorithm-II tuned the task difficulty based on the performance of the participant. Using *%Difficulty(LOW)*, it was noted that the adaptive tuning worked for all participants as reflected by changes in difficulty levels for different segments.

The two aims of Exp-III that followed the pilot study were (i) to evaluate the adaptive algorithm-II with greater number of participants and (ii) to evaluate the adaptive algorithm-II once before the system was tuned according to the adaptive algorithm-I and once after. The participant level analysis shows that the task difficulty levels varied significantly between participants. The participants whose performance significantly differed from majority of the participants who took part in the study were excluded from the analysis and still the difference in performance of the rest of the participants was significant. This supports the findings from PS-III that the task difficulty levels were altered differently by the system for different participants.

The segment level analysis shows the performance as informed by *%Difficulty(LOW)* could identify the differences and similarities in the segments executed by the participants. Segment-3 was the shortest segment and also differed from the rest of the segments in various input conditions. The segment level analysis showed that the performance of the participants during Segment-3 differed significantly from the performance during all the other segments. The pairs Segment-1 & Segment-4 and Segment-2 & Segment-5 are similar in all input conditions but for movement against/towards gravity. The performance of the participants was not significantly different during these segment pairs conforming to the similarities. However, the similarity in the performance identified during Segment-5 & Segment-6 and Segment-6 & Segment-7 pairs does not conform to input conditions during those segments. In summary segment level analysis shows that the performance differences based on the input conditions of the segments executed by the participants could be successfully identified by *%Difficulty(LOW)* in some of the cases, though the same parameter failed to explain in few other cases. It needs further investigations to identify if any other input conditions for the segments other than the ones identified contributed to the variation in performance of the participants.

The performance during active mode (α) and active mode (β) did not differ significantly at the first level analysis with the data from all the participants. The performance did differ when the data from highly influencing participants was excluded and the test of analysis was repeated. This result shows that the performance of the adaptive algorithm-II differed before and after the system was tuned according to the adaptive algorithm-I.

The two sets of the active mode repetitions were separated by the repetitions of the AA2 mode to adapt the task duration according to the adaptive algorithm I. It was highlighted in the results presented in Chapter 4 that the number of repetitions allowed to reach a constant optimum value of duration during various segments need to be personalised. As only a fixed number (five) of the AA2 mode repetitions were executed by the participants during Exp-III (due to constraints of time), this could have contributed to participants becoming influencing factors in the performance evaluation during the active mode (α and β) before and after the AA2 mode repetitions.

The regression results support the finding of varying performance during active mode (α) and active mode (β), despite the R Square (=0.013) being very low. It was evident from segment level analysis of Exp-II that the input conditions of various segments influenced the performance of the participants. These parameters were not included in this regression model as their effect was already studied and established in detail during the analysis of Exp-II data. Exclusion of input parameters could have been a potential contributor to the results of the regression model, especially the low R Square value. The focus of this analysis was to investigate the effect of adaptive algorithm-II during the two sets of the active mode (α / β), the regression results and the performance means plot do show a difference in performance between the two sets of the active modes which was according to the expectations.

A majority of participants responded with a ‘NO/NOT SURE’ for the question ‘difference perceived between first set and last set of the active mode repetitions’. The timing of the questionnaire was a major contributor for these responses as informed by the participants. A separate questionnaire at the end of each set of active mode iterations would have contributed for clearer insight into the difference between the two sets of the active mode iterations as perceived by the participants.

Segment-3 received a highest score of responses for ‘toughest segment to execute’, which conforms with the performance as indicated by *%Difficulty(LOW)* parameter. Similarly Segments 4 and 6 received low scores of responses for ‘toughest segment to execute’, which also complies with the system recorded data. However, the questionnaire responses for other segments were not in compliance with the system recorded data. The PS-III data analysis also highlighted these differences in the participant perception levels and the system recorded data. Therefore we point out that results obtained regarding perceived level of difficulty using questionnaires might not be suited for alignment with the *%Difficulty(LOW)* calculations. Nevertheless, we restate that the parameters like *%Difficulty(LOW)/(HIGH)* could serve as good performance indicators to inform the dynamic changes in the task difficulty levels during interaction sessions.

The responses for ‘usefulness of the embedded objects’ from both PS-III and Exp-III were in favour of embedded set-up. 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 patients.

5.7 Chapter summary

The performance of the adaptive algorithm-II was successfully evaluated with a limited number of participants during pilot study (PS-III) and with a greater number of participants and during Exp-III. The results showed that the task difficulty levels were successfully altered according to the performance of the participants as indicated by the *%Difficulty(LOW)* parameter. In addition Exp-III tested the performance of the adaptive algorithm once before the system tuning according to the adaptive algorithm-I and once after. The results informed a difference in the performance of the participants in the two sets of the active mode repetitions, though the difference recorded was very small. The performance indicator *%Difficulty(LOW)* could also identify the performance differences during various segments based on the input conditions in some cases. The feedback received through questionnaires also informed about the difference in the performance of the system as perceived by the users. The embedded environment was rated as very useful by the majority of the participants. The adaptive algorithm-II 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.

Chapter 6

Summary

This chapter briefly summarises the studies conducted to address the research questions and how the findings from these studies answer the research questions of the PhD. In the end, the chapter also outlines the contribution to knowledge.

6.1 Summary of the Experiments

Three main studies conducted during the course of the PhD are presented in this thesis. The aims of the studies and their key findings are briefly summarised in this section.

6.1.1 Experiment I

Experiment I aimed to investigate if the position data recorded by the HapticMaster could inform the role of the user/robot during a HRI session. The methodology was initially tested during a pilot study with limited number of participants followed by a main experiment with greater number of participants.

PS-I

In the pilot study the investigation was limited to planar point-to-point reaching movements without elevation in order to keep the data analysis simple. The results showed that it is possible to identify whether the HapticMaster robot, or the participant were leading the interaction modelled by the MJT on a single-axis or planar point-to-point movements without elevation at given point in time. When the input conditions changed (such as movements in plane with elevation), the results showed that our approach required further improvements.

Exp-I

Exp-I was designed to test if the vector projections of positional data could inform the leading-lagging of the user interacting with the GENTLE/A system. The experimental protocol was designed to test the modified approach in a 3-dimensional workspace, during which scenarios were created where the participants were asked to intentionally lead or lag the interaction using feedback provided by the graphical user interface, while the robot was programmed to follow the MJT. The $\Delta Effort$ parameter was identified as a potential performance indicator to inform the leading-lagging performance of the user. The type of movement (reaching/returning) involved in executing a point-to-point movement (segment) influenced the performance of the user.

6.1.2 Experiment II

The aim of the research was to augment the adaptability of the GENTLE/A system, so that the users can train at their required pace and comfort. The findings from Exp-I highlight that the users did not always lead the performance when they were asked to do so. In order to adapt the training to user's required pace and comfort, tuning the 'duration' given to execute point-to-point movements was identified as a logical approach. Using the $\Delta Effort$ parameter as a performance indicator we designed an adaptive algorithm to tune the duration given to execute a segment to a user optimum value. Exp-II was designed to evaluate the adaptive algorithm-I during segments with varying input conditions such as reaching-returning movements, moving away-towards gravity, with virtual-embedded target objects and so on.

The results from Exp-II showed that the adaptive algorithm-I could successfully tune the duration to execute a segment to a participant optimum constant value. All the participants managed to reduce the the initial duration set to execute various segments, however, further investigations into influence of the input conditions imposed during various segments executed showed that different patterns of arm movement, as well as different presentation for targets, can influence the durations set to achieve targets.

The segments involving reaching movements required longer execution times when compared to the segments with returning movements irrespective of the influence of gravity. This could possibly be the reason for the participants failing to lead the performance in returning movements in Exp-I. Investigations into underlying kinematics of the upper arm during reaching and returning movements could clarify the difference observed. The results also showed that the execution times for segments with embedded objects as targets were quicker when compared to just virtual targets. This indicated that the embedded targets were better perceived by the participants when compared to the virtual targets shown on the monitor.

6.1.3 Experiment III

Using adaptive algorithm-I the system tuned the task duration according to the user's requirements i.e., the execution time for point-to-point movements is either scaled up or down based on the current requirements of the user. This strategy when transferred to the clinical settings would be more suitable to motivate severely impaired patients in their early stages of recovery.

Once the recovery progresses, a complementary adaptability strategy to make the task challenging is followed in clinical settings. The two parameters that we identified to adapt the task difficulty were, *time given* and *assistance/resistance offered*. Adaptive algorithm-I targets the adaptability based on *time given*. We proposed adaptive algorithm-II that would alter the assistance/resistance offered based on the leading contribution of the user interacting with the GENTLE/A system. This algorithm was evaluated using two strategies (i) study task tuning according to the adaptive algorithm-II in a pilot study (PS-III) and (ii) study task tuning according to the adaptive algorithm-II before and after the system was tuned according to the adaptive algorithm-I in a subsequent main study (Exp-III).

PS-III

The pilot study could successfully evaluate the performance of the adaptive algorithm-II. The new performance indicator *%Difficulty(LOW)* (derived from Δ*Effort* showed a spread of performance between the high and the low task difficulty levels. Comparing questionnaire responses with the 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, it must be noted that perceived difficulty is a subjective measure. Although there are cases where the parameter extracted from questionnaires matches the performance data, there is an assumption that subjective and objective parameters do not always match 100%.

Exp-III

The results from Exp-III with greater number of participants supported the findings from PS-III and showed a spread of performance as informed by *%Difficulty(LOW)* and also the performance differed significantly between participants. The *%Difficulty(LOW)* parameter could also partly identify the differences/similarities in the input conditions imposed during various segments executed during the experiment. The results also showed difference in tuning of task difficulty levels before and after the system was adapted according to the adaptive algorithm-I, though this difference was very small.

Comparing participant perception levels from the questionnaire responses with the system recorded performance data yielded some similarities and differences. Therefore we point out that results obtained regarding perceived level of difficulty using questionnaires might not be suited for alignment with the *%Difficulty(LOW)* calculations. However, we maintain that the parameters like *%Difficulty(LOW)* could serve as useful performance indicators to inform the dynamic changes in the task difficulty levels during interaction sessions. The questionnaire responses from the participants during both PS-III and Exp-III were in favour of embedded set-up rather than just virtual targets displayed on the screen.

6.2 Review of the Research Questions

The results from our studies answered our research questions and in addition explored the influence of various input conditions on the performance of the participants. Moreover, the suitability of the adaptability strategies in clinical settings was keenly considered during the design and implementation of these studies. The research questions that were set prior to the studies are re-presented below:

RQ1: Can the contribution of the user/robot be identified during a HRI session with the GENTLE/A rehabilitation system?

RQ2: Can this identification of contribution be further utilised as a performance indicator?

RQ3: How can the performance indicators be used to improve the adaptability of the

GENTLE/A rehabilitation system?

Our first two studies (PS-I and Exp-I) answered the first research question (RQ1). The parameter recording capability of the HM's sensors was identified as a potential indicator of the role of the user/robot. The first pilot study (PS-I) compared the position data recorded by the HM's sensors with the MJT positions at a given point in time to identify if the user/robot was leading/lagging the interaction. Due to the potential interference of the direction of movement on identifying the leading-lagging performance of the user, we moved to vector projections in the subsequent main experiment (Exp-I). Exp-I could successfully identify the leading-lagging contributions of the user interacting with the GENTLE/A rehabilitation system. In addition Exp-I also informed that the type of the movement involved such as reaching away from/returning towards the body influenced the performance of the users. The lead-lag approach by comparing the robot recorded position with the MJT position is not limited to MJT model and can be reproduced with other models.

The second research question (RQ2) was partially addressed by Exp-I and was successfully answered by Exp-II and PS-III. The sign of the Δ*Effort* parameter identified by the Exp-I could inform the lead-lag role of the user in most of the cases. In the situation of failure of the Δ*Effort* parameter, it was identified that the input conditions imposed during various segments influenced the performance of the user. We designed an adaptive algorithm using Δ*Effort* as a performance indicator that was successfully tested in Exp-II thus answering RQ2. Once the Δ*Effort* parameter identified a leading performance of the user, the parameter *%Difficulty(LOW)* was used to estimate the extent by which a user was leading the interaction. The *%Difficulty(LOW)* was successfully used as a performance indicator during our final pilot study (PS-III).

The two adaptive algorithms designed using the performance indicators identified answered our third research question (RQ3). Apart from the influence of the input conditions, the participants being restricted to perform at their natural pace was identified as potential contributor for difference in performances during Exp-I. In order to address the inherent differences in executing various segments, the adaptive algorithm-I tuned the duration given to execute the segments based on the performance of the user. The results from Exp-II that evaluated the adaptive algorithm-I showed that the GENTLE/A system could successfully tune the duration required to execute various point-to-point reaching tasks according to the user's requirement. Furthermore, Exp-II also identified that reaching movements required longer durations when compared to returning movements. This could be an important consideration for studies applying a set duration to achieve reaching and returning trajectories.

The adaptive algorithm-II was designed to address a complementary adaptability strategy to challenge the user once the user starts to consistently lead the interaction. Depending on the extent of leading contribution, the adaptive algorithm-II altered the difficulty level of the task. The results from PS-III and Exp-III showed a spread of performance of the participants between high and low task difficulty levels based on their leading contributions. This informed that the system adapted the task difficulty levels based on the performance of the user. Exp-III also explored the difference in the tuning of the task difficulty levels before and after the task duration was adapted according to the first adaptability strategy.

6.3 Summary of Contribution to knowledge

The key contributions of this research can be summarised as:

1. Utilised the parameter recording capability of the HM's sensors to identify the role of the user/robot during a HRI session. This is a vital achievement in the wake of the major reviews (summarised in Chapter 2) in the area of upper-limb rehabilitation

robotics identified the potential of parameter capturing capability of robots and its current under-utilisation.

2. Proposed an adaptability strategy that would auto-tune the task duration according to the user's requirement. The auto-tuning was accomplished by tuning the duration set to execute point-to-point reaching tasks, the distinct methodology implemented for the first time. This would allow the users to perform the task at their natural pace and comfort and we believe this would help in motivating the users in the initial stages of recovery in rehabilitation settings.

3. Introduced a complementary adaptability strategy that would alter the challenge in the task based on the performance of the user. Although this strategy of regulating task difficulty was proposed and evaluated by a different research group, during our research the parameters that were altered to achieve task regulation and the set-points for task regulation were different and also proved to be successful in our studies. This strategy is thought to be suitable to offer rehabilitation training for less impaired users.

4. The improved performance of the users in embedded environments identified by our studies is a key finding in designing the experimental set-ups to offer rehabilitation trainings. The virtual worlds were perceived as relatively more difficult by the participants with good cognitive abilities who took part in our studies. Considering the stroke patients with impaired cognitive abilities, it is thought that an embedded set-up would be cognitively less demanding when compared to a complete virtual set-up and might encourage and assist the participant in performing better during a therapy session.

5. Our studies identified differences in the performance of the participants during point-to-point reaching tasks based on the type of movements involved such as reaching-

returning, large-small cross-body movement and so on. These findings would contribute vital information to research exploring the kinematics of upper-arm.

Chapter 7

Conclusions

7.1 Conclusions

The main aim of the research presented in this thesis was to enhance the adaptability of the GENTLE/A rehabilitation system. The adaptability of a rehabilitation system is key to facilitate the users to train independently with minimal supervision from the therapist. This is believed to promote the training times and thereby the recovery by motivating the users to train more.

In order to augment the adaptability of the system according to the performance of the user, we followed the path of utilising the parameter recording capability of the HapticMaster robot. The positional data recorded by the HapticMaster robot was compared with the MJT positions and this could effectively inform the leading-lagging performance of the user during a HRI session.

The preliminary studies (PS-I and Exp-I) conducted during this PhD were not only successful in role identification but also identified other conditions that might influence the performance of the user. The next study (Exp-II) evaluated if the role (leading/lagging) identification could be utilised as a performance indicator to tune the system. Adaptive algorithm-I could effectively utilise the performance indicator to adapt the duration given to execute point-to-point movements to user's specific optimum value. In summary the adaptability of the GENTLE/A system was enhanced to tune the task time according to the user's requirement.

Our final studies (PS-III and Exp-III) explored a complementary adaptability strategy to alter the challenge in the task according to the performance of the user. Adaptability algorithm-II could successfully utilise the performance indicators to identify the leading role of the user and tune the task difficulty level. The extent of lead identified by the performance indicator was successfully used to scale (up/down) the difficulty level of the task being performed. Exp-III also explored the difference in the tuning of the task difficulty levels before and after the task duration was adapted according to the first adaptability strategy.

In conclusion, our research during this PhD could successfully enhance the adaptability of the GENTLE/A rehabilitation system. Moreover the adaptability strategies evaluated were designed to suit various stages of recovery in rehabilitation settings. The parameters that would influence the performance of the users such as various movement types (reach-return, large-small cross-body movement), various presentation of targets (virtual-embedded) could become key contributors to the design of experimental set-ups and studies in clinical settings.

7.2 Limitations

The studies conducted during this PhD included participants who willingly volunteered to take part in the experiments. Due to the duration ($\approx$45min) and location (restricted to the Robotics lab in the university premises) constraints of the experimental session, the majority of the participants in our studies belonged to the student community (mostly young adults) at the university. The studies therefore did not benefit from representation of participants from a wider spread of age, ability and backgrounds. Furthermore, the participants usually being healthy young adults tried to scale up to the challenge offered by the task even when they were asked to remain passive and allow the robot to take charge of the activity. This led to a greater amount of leading performance data and a comparatively smaller amount of lagging performance data.

The participants were restricted to perform a fixed number of repetitions of each mode due to the limitations of time to conduct an experimental session. In the opinion of the author, this could have influenced the results. During Exp-II the active-assisted mode was executed five times, while the adaptive algorithm-I tried to tune the duration to participant specific optimum value. The results showed that some of the segments could reach a constant optimum value of duration, while others were still tuning. The shorter (length) segments needed smaller durations when compared to longer segments and hence needed more repetitions to scale down to optimum value. Allowing varying tuning time depending on the nature of the segment would have given a better evaluation of the adaptive algorithm-I.

Adaptive algorithm-II varied the task difficulty level by varying the spring stiffness. The stiffness values for high and low task difficulty levels were set to optimum values after series of tests before the main experiment. These stiffness levels however did not match the participant perceived high and low task difficulty levels with some of the participants. It would have been ideal if the training session was utilised to assess the base performance of the participant and the stiffness values were set according to the perceived difficulty during the training session.

7.3 Future direction

The studies during this PhD did not benefit from impaired patient's participation, however the research focussed on providing a platform where the adaptive interfaces could self-tune to individual's performance. The crucial step that could enhance the value of the findings from this PhD would be evaluating the adaptability strategies developed in clinical settings. Conducting clinical trials with the GENTLE/A rehabilitation system with upper-limb impaired users in various stages of recovery provides an opportunity to test the usefulness of the adaptive algorithms designed during this PhD.

The adaptability strategies developed were mainly based on the position data recorded by the HM's sensors. The velocity data was used briefly in Exp-I to support the findings from position data analysis. The velocity and force data recorded by the HM's sensors might offer further insights into the performance of the user that could strengthen the findings from our studies.

The influence of movement types involved in executing various segments on the performance of the user needs further investigations. Exploring the muscle groups involved in achieving various upper-arm movements (using techniques like EMG) would elaborate more on the differences observed in the performance of various segments by the participants during our studies. Studying the kinematics of upper-arm and its influence on point-to-point reaching tasks forms part of future work.

The adaptive algorithms developed would suit any rehabilitation training system that uses a reference trajectory to guide the movement training. Developing an open source code of the adaptive algorithms that is platform independent could facilitate clinical trials on variety of rehabilitation systems and offer valuable feedback on the usefulness of the strategies in clinical settings.

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Appendix I

Table A. Adaptation of segment durations in the AA2 mode (Exp-II)

Participant	Mode	Iteration	Seg-1	Seg-2	Seg-3	Seg-4	Seg-5	Seg-6	Seg-7	Seg-8	Seg-9	Seg-10	Seg-11	Seg-12	Seg-13	Iteration Level*
1	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	3	3.2	3	3.2	3	3.6	3	3.6	3	3	3.6	3	3.2	
		2	2.6	2.8	2.4	2.8	2.6	3.2	2.6	3.2	2.6	2.8	2.6	2.8	2.8	
		3	2.6	2.8	2.4	2.6	2.8	2.2	2.4	3	2.4	2.4	2.6	2.6	2.8	
		4	2.4	2.8	2.6	2.6	2.8	2.2	2.6	3	2.4	2.4	2.6	2.6	2.8	
		5	2.6	2.8	2.6	2.6	2.8	2.2	2.6	3	2.6	2.4	2.6	2.6	2.8	11
2	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	3.4	3	3	3	3.6	3.8	3	3.8	3.4	3	3	3.6	3	
		2	2.4	2	2.2	2	2.6	2.8	2	2.8	2.6	2.8	2.6	2.6	2	
		3	2.2	1.6	1.8	1.6	2.4	1.8	1.8	1.8	2.2	2.8	1.6	2.2	1.6	
		4	1.8	1.6	1.6	1.2	2.4	1.6	1.6	1.6	2	2.6	1.2	2	1.6	
		5	1.6	1.6	1.6	1	2.4	1.6	1.6	1.6	1.8	2.6	1	2	1.6	9
3	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	3.2	3.8	3.2	4.4	3.6	4.2	3.2	3.6	3.2	6	4.4	4.2	3.4	
		2	3.2	3.8	3.2	4.6	3.8	5.2	3.2	3	3.2	7	4.8	4.4	2.8	
		3	3.2	3.2	3.2	5	4	4.2	3.2	3.4	3.2	8	4.8	4.6	3.2	
		4	3.2	3.6	3.2	4.4	4.4	4.2	3.2	3.6	3.2	9	3.4	4.4	3.8	
		5	3.2	4.2	3.4	3.8	4.6	4.6	3.4	3.8	3.2	9	3.8	4.4	4.2	4
4	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	3	3	4.2	3.4	4.4	4	3.8	3	3	3.4	3.4	3	3	
		2	3	2.8	2.8	3.4	3.4	4	2.6	3	3	3.4	3.6	3	2.6	
		3	3	2.6	2.6	3.6	3.4	3.8	2.6	3.2	3	3.4	3.6	3	2.6	
		4	2.6	2.6	2.8	3.4	3.2	3.4	3.2	3.2	3	3.8	3.8	3	2.8	
		5	3.2	2.4	3.2	3.6	3	3.4	3.2	3.2	3.2	3.4	3.6	2.8	2.4	3
5	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	4	4	4	4	4	4	3	4	3.8	4	4	4	4	
		2	2.8	3	2.8	3.6	3	4	2.6	4	2.8	3.6	3.4	3	3	
		3	2.8	3	2.6	3	3	3.8	2.6	3.8	2.8	3.6	3	3	3.2	
		4	2.8	3.2	2.6	2.8	3	3.6	2.6	3.6	2.8	3.6	2.8	3	3.2	
		5	2.8	2.8	2.6	2.4	3	3.4	2.6	3.4	2.8	3.4	2.4	2.8	2.8	5

Table A. Adaptation of segment durations (seconds) during the five iterations of the AA2 mode for all the participants (Exp-II)

Participant	Mode	Iteration	Seg-1	Seg-2	Seg-3	Seg-4	Seg-5	Seg-6	Seg-7	Seg-8	Seg-9	Seg-10	Seg-11	Seg-12	Seg-13	Iteration Level*
6	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	4.6	4.8	4.6	4.8	4.4	4.2	4.6	4.2	4.6	4.2	4.8	4.2	4.8	
		2	4.8	4.8	4.8	5.2	4.6	4.4	4.8	4.4	5	4.6	5.2	4.4	5	
		3	5.2	5.4	4.8	5.2	4.6	4.6	5.2	4.6	5.4	4.8	4.2	4.4	5.4	
		4	5.4	5.4	5.2	4.2	4.2	4.6	5.2	4.6	5.2	5	4.2	4.6	5.4	
		5	5.2	5.4	5.2	4.2	4.4	4.4	5.4	4.6	5.2	5.2	4.4	4.6	5.2	6
7	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	4	4	3.6	4.2	4	3.8	3.6	4	4	4.4	3.2	4	5	
		2	4	4	4	3.6	3.8	3.8	3.8	3.8	4	4.8	3.2	4	3	
		3	4.4	3.2	4.2	4.2	4	3.8	4.2	3.8	4.4	4.8	4.2	4	3.6	
		4	4.2	3.6	4	4.2	4.4	3.8	3.8	3.6	4.2	4.8	4.2	4	3.4	
		5	4.2	3.4	3.8	4	4.4	3.8	3.8	3.6	4.2	4.6	4	4	3.4	8
8	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	4	4	4	4	4	4	3	4	3	4	3.6	4	3.2	
		2	2	3.2	2.8	3.2	3	3	1.8	3	1.6	3	2.4	3	2.2	
		3	1.2	2.2	1.8	2.2	2.6	2	2	2.6	1.2	2.8	2.2	2.8	2	
		4	1.6	2.4	2	2.2	2.6	2.4	2.2	2.6	1.4	2.8	2.2	2.8	2.6	
		5	1.8	2.2	2.2	2.2	2.8	2.2	2.2	2.6	1.8	2.6	2.2	1.8	2.2	4
9	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	3.8	3.2	3.8	3	4	3	3.8	3	3.6	3.8	3	4	3	
		2	3.6	2.8	2.8	2.8	4	2.8	2.8	2.8	3.6	4	2.8	4	2.6	
		3	3.6	3	3	2.8	4	2.8	3	2.8	3.6	4.2	2.6	4.2	3	
		4	3.6	3.2	3	2.4	3.8	2.8	2.6	2.8	3.4	4.2	2.4	4.2	2.2	
		5	3.4	2.6	2.6	2.4	3.8	2.6	2.6	2.8	3.4	4.4	2.4	4.2	2.6	7
10	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	4	3.2	3.4	3	4.4	3	3.4	3.6	3.8	3.8	3.2	4	3.6	
		2	2.8	2.8	2.4	2.8	4.2	2.8	2.6	2.6	2.8	3.4	3	3.8	1.8	
		3	2.8	2.2	2.6	3	3.2	2.8	2.6	2.8	2.8	3.4	3	3.8	1.2	
		4	2.6	1.6	2.6	3	3.2	2.8	2.8	2.8	2.8	3.2	3	3.8	2	
		5	2.6	2.4	2.8	3	3.2	2.6	2.8	2.8	2.6	3.4	3	3.8	2.4	7

Participant	Mode	Iteration	Seg-1	Seg-2	Seg-3	Seg-4	Seg-5	Seg-6	Seg-7	Seg-8	Seg-9	Seg-10	Seg-11	Seg-12	Seg-13	Iteration Level*
11	AA1	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	3.6	2.6	3.4	3.4	3.8	3	3	3	3.6	4.2	3	3	3	
		2	3.4	2	2.8	2.4	3.8	2.6	2.8	2.8	3.4	4.2	2.2	2.8	2	
		3	2.4	2	2.2	1.4	3	2	2	1.8	2.6	3.2	1.4	2.4	2	
		4	2.4	2	2	1.6	2	2	2	1.6	2.4	2.6	1.8	2.2	2	
		5	2.4	2.4	2	1.8	2	2	2	1.8	2.4	2.4	1.8	2	2.4	7
12	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	3.2	3.6	3.8	3.2	4.2	4	3.8	4	3.6	4.4	3.2	4.2	3.6	
		2	2.6	2.8	3.4	3.2	4.2	3.8	3.6	3.8	3	4.8	3.2	4.2	3	
		3	3.2	3.4	3.6	3.2	4.2	4	3.6	4.2	3.6	4.8	3.2	4.2	3.4	
		4	3.8	3.4	4	2.8	4.2	4.2	4	4.4	4.2	4.8	2.8	4.4	3.6	
		5	4.2	3.8	3	2.6	3.8	4.2	3	4.4	4.2	4.8	2.6	4.4	3.8	5
13	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	4.6	4.8	4.6	4.8	4.4	4.4	4.6	4.4	5	4.4	5	4.4	4.8	
		2	5.2	5.2	5	5.4	4.8	4.8	5.2	4.6	5.4	4.8	5.4	4.6	5.2	
		3	5.6	5.6	5.4	5.8	5.2	5	5.2	5	5.6	5	4.8	4.8	5.2	
		4	5.6	5.4	5.2	5	5.2	5.2	5.2	5	5.6	5.2	5	5	5.2	
		5	5.8	5.2	5.2	5	5.6	5.4	5.2	5	5.8	5.4	5	5.2	5.2	6
14	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	4	4	4	4	4	4	3	4	3.6	4	3	4	3	
		2	2.6	2	2.6	2	3	3	1.6	3	2.6	3	2	3	1.6	
		3	2.4	1.6	2	1.6	2	2	2	2.2	2.6	2.8	1.8	2.4	1.6	
		4	2.4	2	1.4	1.8	2.2	2.2	1.4	2.4	2.6	3	1.8	2.4	1.6	
		5	2.4	2	1.8	1.6	2.2	2	1.8	2.4	2.4	3	1.6	2.4	2	6
15	AA2	Default	4	4	4	4	4	4	4	4	4	4	4	4	4	
		1	3	3	3	3	4	4	3	4	3	4	3	4	3	
		2	2	2	2	2.6	3	3	2	3	2.4	3	2.6	3	2	
		3	2.4	2.4	2	2.8	2.8	3	2	3	2.8	3	2.8	3	2.4	
		4	2.8	2.4	2.2	2.8	3	2.8	2.2	3	2.6	3.4	2.6	3	2	
		5	2.4	2	2	2.6	2.8	2.4	2	3	2.4	3.4	2.6	2.6	2	4

Table A. Adaptation of segment durations (seconds) during the five iterations of the AA2 mode for all the participants (Exp-II)

Participant	Mode	Iteration	Seg-1	Seg-2	Seg-3	Seg-4	Seg-5	Seg-6	Seg-7	Seg-8	Seg-9	Seg-10	Seg-11	Seg-12	Seg-13	Iteration Level*
16	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3	2.8	2	2.8	3	3	2	3	2.6	3.4	2.6	3.4	2.6	
		2	2.6	2.6	2	2.6	3	3.2	2	3.2	2.8	3.6	2.6	3.6	2.6	
		3	3	2.2	2.2	2.4	3	3.2	2.2	3.2	3	4	2.2	3.6	2.2	
		4	3.2	2.2	2.4	2.2	3.2	3.2	2.2	3.2	2.2	3.8	2.2	3.4	2.4	
		5	2.2	2.6	2.2	2.2	2.8	3.2	2.2	3.2	2.2	3.8	2.2	3.2	2.6	7
17	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3.4	3.6	3	3.2	3.2	3.4	2.6	3.4	3.4	3.4	3.2	3.2	3.4	
		2	3.2	3.6	2.6	3.2	3.2	3.4	2.8	3.6	3.2	3.6	3.2	3.2	3.4	
		3	3	3.6	2.8	3.2	3.2	3.4	2.6	3.8	3	3.6	3	3.2	3.2	
		4	2.8	3.4	2.6	3.2	3	3.4	2.4	3.8	3.2	3.6	3.2	3.2	3.4	
		5	3	3.4	2.4	3.2	3	3.4	2.4	3.8	3	3.4	3.2	3.2	3.4	9
18	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3	3	3	3	3	3	3	3	3.2	3	3.2	3	3	
		2	2	2	2.4	2.6	2.8	3.2	2.4	3	2.4	3.6	2.8	3.4	2	
		3	2	1.6	2.4	2.8	2.4	2.8	2.6	2.8	2.4	3.6	3	3.4	1.8	
		4	2.4	1.8	2.2	3	2.4	2.6	2.6	2.6	2.6	3.6	3	3.2	2	
		5	2.2	2	1.6	3	2.4	2.6	1.6	2.4	2.2	3.6	3	3.2	2	7
19	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	2.8	2	2.6	2.6	2.6	2.8	2.6	3	2.8	3.4	2.6	3	2.6	
		2	1.8	1.8	2.2	1.8	2.6	2.6	2.2	3	2.2	3.4	1.6	3	1.8	
		3	1.8	1.4	1.2	1.6	2.6	2.2	1.6	2.6	2.2	3.2	1.8	3	1.6	
		4	2.2	1.6	1.8	1.8	2.8	2.4	1.8	3	2.4	3	1.8	3	1.6	
		5	2.2	1.6	1.8	1.8	2.6	2.2	1.8	2.8	2.2	2.8	1.8	3	1.6	8
20	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	2.6	3.2	2.8	3.2	3.2	3	3.2	3	2.8	3.4	3.6	3.4	3.4	
		2	2.8	3.6	3.4	3.8	3.6	3.4	3.8	3.4	2.8	3.8	4.2	3.8	3.8	
		3	2.8	4	4.2	4.4	4	3.8	4.4	3.8	3.2	4.2	4.8	4.2	4.4	
		4	3.2	4.8	4.6	5	4.4	4.2	4.6	4.2	3.4	4.6	5.2	4.6	4.6	
		5	3	4.6	5	5.4	4.4	4.6	5	4.4	3	5	5.4	5	4.6	2

Participant	Mode	Iteration	Seg-1	Seg-2	Seg-3	Seg-4	Seg-5	Seg-6	Seg-7	Seg-8	Seg-9	Seg-10	Seg-11	Seg-12	Seg-13	Iteration Level*
21	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	2.4	2.2	2.8	2.4	2.8	2.6	2.8	2.8	2.6	2.6	2	2	2.2	
		2	2.4	1.8	1.8	1.8	1.8	2.2	2.2	2.4	2.8	2.6	1.8	2	2	
		3	1.8	2	2	2	1.8	2.2	1.8	2.4	2.2	2.2	1.8	2	1.8	
		4	2	1.4	1.6	1.8	1.6	1.8	1.4	2	2.2	1.8	1.6	1.6	1.4	
		5	1.8	1.4	1.4	1.6	1.4	1.6	1.4	1.8	1.8	1.6	1.6	1.4	1.4	4
22	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3.4	3.4	3.6	3.6	3.4	3.2	4	3.4	3.6	3.4	3.8	3.4	3.6	
		2	3.6	3.6	4	3.8	3.8	3.4	4.4	3.6	3.8	4.4	4	3.8	3.6	
		3	3.8	3.6	4	4	4	3.8	4.4	3.8	4	4.8	4	4.2	3.6	
		4	3.8	3.6	4	3.8	4	3.8	4.4	3.8	3.8	5.2	3.8	4.6	3.6	
		5	2.8	3.2	4	3.8	4	4	4	3.8	2.8	6.2	3.8	5	3.2	5
23	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3.2	3.2	3.2	3.2	3.4	3.4	3.2	3.4	3.4	3.4	3.4	3.2	3.4	
		2	3.4	3.6	3.4	3.6	3.6	3.4	3.6	3.8	3.6	3.8	4	3.4	3.6	
		3	3.6	3	3.8	3.8	3.8	4	4	4.2	4	4.6	4	4	3.2	
		4	3.8	3.4	4	4.2	3.8	4	4	4.2	4	5	4.2	4.4	3.6	
		5	3.8	3.8	4	4.4	4	4.4	4	4.6	3.8	5.4	4.4	4.4	3.8	4
24	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3.4	3	3	3.6	3.2	3.2	2.8	3.4	3.6	4	3.8	3.2	3	
		2	3.6	3	2.8	3.6	3.2	3.4	2.8	3.8	3.8	4	3.4	3.2	3	
		3	2.8	2.6	2.8	2.4	3.2	3.4	2.8	3.6	3	3.6	2.4	2.8	2.6	
		4	3	2.6	2.8	2	3.4	3.2	2.4	3.4	3	2.6	2	2.8	2.4	
		5	3	2.4	2.2	2	3.4	2.8	2.2	3.2	3	2.4	2	2.8	2.4	7
25	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	2.2	2	1.8	2.2	2	2	2	2.6	2.4	2.8	2.6	2	2.8	
		2	2.2	1.8	1.6	2	2	2	1.4	2.2	2.4	3.2	1.8	2	1.8	
		3	2.4	2	1.6	2	2	2	1.6	2.2	2.4	3	2	2	1.8	
		4	2.2	1.8	1.8	2	2.2	2.4	1.8	2.2	2.2	2.8	2	2	1.8	
		5	2.2	1.8	2	2	2.4	2.8	2	2.2	2.2	3	2	2	1.8	8

Table A. Adaptation of segment durations (seconds) during the five iterations of the AA2 mode for all the participants (Exp-II)

Participant	Mode	Iteration	Seg-1	Seg-2	Seg-3	Seg-4	Seg-5	Seg-6	Seg-7	Seg-8	Seg-9	Seg-10	Seg-11	Seg-12	Seg-13	Iteration Level*
26	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	2.8	2.8	3.2	3.2	3.4	3	3.4	3.4	2.8	3.4	2.8	4	2.6	
		2	2.8	3	3.4	3	4.4	3.2	3.8	3.6	3	3.8	3	4.4	2.8	
		3	2.6	2	3.4	2.6	4.6	3.2	3.6	3.6	3	4.2	3	4.4	2.2	
		4	2.8	2.4	3.6	3	4.6	3.6	2.6	4	2.8	4.6	3	4.4	2.4	
		5	2.6	2.4	2.6	3	3.6	3.6	2.6	3	2.6	5	3	5.4	2.4	6
27	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3.4	2.2	3	3	3	3	2.6	3	3.4	2.6	2.6	2.8	2	
		2	3.4	2	2.4	2.6	2.8	2	2.2	2.8	3.4	2.6	2.4	2.8	2	
		3	3	1.6	2.2	2	2.6	2	2	2.6	3	2.6	2	2.6	1.6	
		4	2.8	1.6	2.2	2	2.4	2	2	2.6	2.8	2.6	1.8	2.6	1.6	
		5	2.8	2	2	1.8	2.6	2	2	2.6	2.8	2.8	1.8	3	2	6
30	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3.2	2.8	2.4	2.8	3.2	3	2	3.2	3.2	3	2.6	3.2	2.6	
		2	3	2.2	2	2.4	2.8	2.8	1	3.2	3	2.8	2.4	2.8	2	
		3	3	2.2	1.2	2.4	2.8	2.4	1.4	3.2	3	3	2.4	2.8	1.8	
		4	2.8	2.2	1.6	2.4	2.8	2.4	1.6	3	2.8	3	2.4	2.8	2	
		5	2.8	2.2	1.8	2.4	2.8	2.2	1.8	2.8	2.8	3	2.4	2.6	2.2	7
31	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3.4	3.6	3.6	3.6	3.4	3.4	3.6	3.4	3.8	3.4	3.8	3.4	3.8	
		2	4	4	4	4	3.8	3.8	4.2	3.8	4.2	3.8	4.4	3.8	4	
		3	4.2	4.4	4.4	4.6	4.2	4	4	4.2	4	4.2	4.8	4.2	4	
		4	3.6	4	4.2	4.6	4.4	4.2	3.8	4.4	3.6	4.4	4.6	4.4	4	
		5	3.6	4.4	3.8	4.6	4.4	4.4	3.8	4.4	3.6	4.6	4.6	4.6	4.4	7
32	AA2	Default	3	3	3	3	3	3	3	3	3	3	3	3	3	
		1	3	3	2.2	2.6	2	2.8	2.2	3.2	2.8	3	2.6	2	3.2	
		2	2.6	3.2	2.2	2.6	2.2	2.8	1.8	3	2.6	3.2	2.6	2.2	3.2	
		3	2.6	3.2	2	2.6	2.6	3	2	3	3	3.4	2.6	2.4	3.2	
		4	3	3.4	2.2	2.6	2.8	3.2	2	3.4	3	3.4	2.8	2.6	3	
		5	3	3.4	2.2	3	3	3.2	2.2	3.4	3	3.4	3	2.8	3.4	7
		Segment Level**	14	11	10	16	15	12	18	19	14	10	19	15	13	

Iteration Level - Number of segments that reached to a constant optimum value of duration within five repetitions of the AA2 mode for each participant

Segment Level - Number of participants who could reach a constant optimum value of duration within five repetions of the AA2 mode for each segment

Table B. Coefficients of regression models 1 and 2

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
Model 1	(Constant)	7.457	.222		33.617	.000
	Embedded	-.650	.081	-.120	-8.027	.000
	Reach	.851	.076	.157	11.214	.000
	Towards Gravity	.399	.095	.068	4.206	.000
	Ground Level	.920	.091	.157	10.091	.000
	Small	-.151	.078	-.028	-1.950	.051
	Subject 2	-1.563	.276	-.117	-5.669	.000
	Participant 3	3.003	.284	.211	10.572	.000
	Participant 4	1.471	.284	.103	5.178	.000
	Participant 5	.838	.309	.050	2.710	.007
	Participant 6	4.903	.295	.319	16.630	.000
	Participant 7	2.891	.295	.188	9.805	.000
	Participant 8	-.390	.284	-.027	-1.374	.170
	Participant 9	1.073	.295	.070	3.640	.000
	Participant 10	.566	.295	.037	1.921	.055
	Participant 11	-.662	.284	-.046	-2.329	.020
	Participant 12	2.362	.295	.154	8.013	.000
	Participant 13	5.587	.295	.364	18.950	.000
	Participant 14	-1.445	.284	-.101	-5.087	.000
	Participant 15	-.340	.295	-.022	-1.154	.249
	Participant 16	-.379	.295	-.025	-1.285	.199
	Participant 17	.748	.295	.049	2.536	.011
	Participant 18	-.597	.295	-.039	-2.024	.043
	Participant 19	-1.449	.295	-.094	-4.914	.000
	Participant 20	2.323	.295	.151	7.879	.000
	Participant 21	-2.114	.295	-.138	-7.171	.000
	Participant 22	2.230	.295	.145	7.564	.000
	Participant 23	2.091	.284	.147	7.362	.000
	Participant 24	.264	.295	.017	.895	.371
	Participant 25	-1.835	.295	-.119	-6.224	.000
	Participant 26	.818	.295	.053	2.775	.006
	Participant 27	-.930	.295	-.061	-3.154	.002
	Participant 30	-.826	.295	-.054	-2.801	.005
	Participant 31	2.682	.295	.175	9.099	.000
	Participant 32	-.079	.294	-.005	-.269	.788
Model 2	(Constant)	6.358	.215		29.597	.000
	Embedded	-3.477	.167	-.641	-20.841	.000
	Reach	4.433	.167	.817	26.606	.000
	Towards Gravity	.117	.289	.020	.404	.686
	Ground Level	1.831	.167	.312	10.991	.000
	Small	.729	.167	.134	4.377	.000
	Participant 2	-1.563	.242	-.117	-6.470	.000
	Participant 3	3.003	.249	.211	12.065	.000
	Participant 4	1.471	.249	.103	5.909	.000
	Participant 5	.838	.271	.050	3.092	.002
	Participant 6	4.903	.258	.319	18.978	.000
	Participant 7	2.891	.258	.188	11.190	.000

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
Participant 8	-.390	.249	-.027	-1.568	.117
Participant 9	1.073	.258	.070	4.153	.000
Participant 10	.566	.258	.037	2.192	.028
Participant 11	-.662	.249	-.046	-2.658	.008
Participant 12	2.362	.258	.154	9.145	.000
Participant 13	5.587	.258	.364	21.626	.000
Participant 14	-1.445	.249	-.101	-5.805	.000
Participant 15	-.340	.258	-.022	-1.316	.188
Participant 16	-.379	.258	-.025	-1.467	.143
Participant 17	.748	.258	.049	2.894	.004
Participant 18	-.597	.258	-.039	-2.309	.021
Participant 19	-1.449	.258	-.094	-5.608	.000
Participant 20	2.323	.258	.151	8.991	.000
Participant 21	-2.114	.258	-.138	-8.184	.000
Participant 22	2.230	.258	.145	8.632	.000
Participant 23	2.091	.249	.147	8.402	.000
Participant 24	.264	.258	.017	1.022	.307
Participant 25	-1.835	.258	-.119	-7.103	.000
Participant 26	.818	.258	.053	3.167	.002
Participant 27	-.930	.258	-.061	-3.600	.000
Participant 30	-.826	.258	-.054	-3.197	.001
Participant 31	2.682	.258	.175	10.384	.000
Participant 32	-.065	.258	-.004	-.253	.800
EV1G1	4.193	.334	.653	12.569	.000
EV1G2	2.831	.264	.377	10.732	.000
RR1G1	-2.682	.289	-.358	-9.280	.000
RR1G2	-3.759	.204	-.501	-18.401	.000
RR1CB1	-1.361	.236	-.212	-5.770	.000
G1CB1	-.390	.236	-.052	-1.653	.099
G2CB1	.345	.167	.046	2.068	.039

Table C. Tukey's test *Participant, %Difficulty(LOW)* (Exp-III)
Provided in a CD with the thesis

Table D. Tukey's test *Segment, %Difficulty(LOW)* (Exp-III)
Provided in a CD with the thesis

Appendix II

Questionnaire (PS-III)

1. How do you rate the challenge in the task? (Please circle)

1	2	3	4	5
Not at all Challenging	Not very Challenging	Neutral	Somewhat Challenging	Very Challenging

2. Which 'Point' was the toughest to reach?

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐

3. How to do you rate the usefulness of the embedded object (numbered stickers) alongside the virtual target displayed on the monitor? (Please circle)

1	2	3	4	5
Not at all Useful	Not very Useful	Neutral	Somewhat Useful	Very Useful

4. Did you feel any difference in executing the task as the movement progressed from source to target?

Yes ☐ No ☐

5. If yes, can you briefly explain the difference felt by you?

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6. Additional comments or suggestions:

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Participant ID: _ _

Questionnaire (Exp-III)

1. Which ‘Point’ was the toughest to reach?

1	2	3	4	5	6	7	8
☐	☐	☐	☐	☐	☐	☐	☐

2. How to do you rate the usefulness of the embedded object (numbered stickers) alongside the virtual target displayed on the monitor? (Please circle)

1	2	3	4	5
Not at all Useful	Not very Useful	Neutral	Somewhat Useful	Very Useful

3. Did you feel any difference between the first 3 and the last 3 repetitions of the active mode?

Yes ☐ No ☐

4. If yes, can you briefly explain the difference felt by you?

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5. Additional comments or suggestions:

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