Real-time monitoring and registration of brain shift using hybrid control strategy for robotic neurosurgery

Vineet Jacob Kuruvilla

2013

Vineet Jacob Kuruvilla. (2013). Real-time monitoring and registration of brain shift using hybrid control strategy for robotic neurosurgery. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/53098>

<https://doi.org/10.32657/10356/53098>

NANYANG
TECHNOLOGICAL
UNIVERSITY

**REAL-TIME MONITORING AND REGISTRATION OF BRAIN SHIFT
USING HYBRID CONTROL STRATEGY FOR ROBOTIC NEUROSURGERY**

VINEET JACOB KURUVILLA

SCHOOL OF MECHANICAL AND AEROSPACE ENGINEERING

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USING HYBRID CONTROL STRATEGY FOR ROBOTIC NEUROSURGERY**

VINEET JACOB KURUVILLA

School of Mechanical and Aerospace Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

2013

ABSTRACT

Brain, being a soft tissue, deforms dynamically during neurosurgery. Maximum displacement of 50mm at the end of tumour resection surgery (6-7 hours) has been observed in some studies. This phenomenon of intra-operative brain tissue deformation is called brain shift. Currently available non-invasive neurosurgery robotic systems such as Cyberknife®, assumes a fixed spatial relationship between brain abnormalities like brain tumour and the skull. This can lead to inaccurate targeting due to brain shift when using non-invasive surgical modalities such as High Intensity Focused Ultrasound (HIFU). Frequent tracking of the brain shift followed by dynamic update of the treatment plan needs to be performed for positional compensation.

In this research, a control framework for non-invasive neurosurgical robots, using dynamic image registration for tracking the intra-operative deformation of the brain in real-time is devised. The estimation of intra-operative deformations of the brain tissues are addressed for improving the accuracy. A two-stage dynamic deformation tracking strategy was developed in this work for the intra-operative brain shift estimation using a fast and computationally light template matching algorithm for the rigid shift estimation (gross position information) and a more computationally intensive point-based non-rigid image registration algorithm called coherent point drift algorithm (CPD) for the non-rigid shift estimation (fine position information). For the experimental testing, ultrasound imaging was used as the intra-operative imaging modality and phantoms made of agar agar gel with embedded target were used. An average error of 0.4mm and average computation time of 0.8second was obtained from template matching algorithm and average error 1.94mm with a computation time of approximately 72.7seconds for the coherent point drift algorithm. The computation time was reduced by a factor of 5 to 9 by introducing a down-sampling factor to the number of points in the registered point sets.

A hierarchical hybrid supervisory control combining a supervisor, direct model reference adaptive control (DMRAC) and proportional-integral-derivative (PID) control for non-invasive neurosurgical robots is proposed. The control architecture consists of three layers- the high level supervisor, mid-level and the low level control. The PID controller and DMRAC were formulated, simulated, implemented and tested and the performances were compared. DMRAC showed 22% better accuracy compared to PID controller in workspace regions where the dynamic effects (friction, moment of inertia variations) were significant especially in the Distant Point protocol. In workspace regions or Adjacent Point protocol where the dynamic effects were minimal, both PID controller and DMRAC showed comparable performance. The control derivation of the hybrid supervisory control, its simulation and experimental testing was performed. The results showed better accuracy compared to using a standalone PID controller by switching to DMRAC when the performance of PID controller deteriorated. The accuracy of the overall system was 22% better compared to the performance of PID controller in Distant Point protocol and no significant advantage in Adjacent Point protocol. The proposed control is tested on the end-effector of a representative neurosurgical robot, FUSBOT-NS (Focused Ultrasound Surgery Robot-Neurosurgery).

ACKNOWLEDGEMENT

First of all, I would like to convey my sincere appreciation to my supervisors Assoc. Prof. Sunita Chauhan and Assoc. Prof. Louis Phee Soo Jay. A/P Sunita has been a great source of encouragement and guidance from the time of my joining. Without her support, this research would not have been possible. I am particularly grateful to her for continuing to support me even after she left NTU. I specially thank A/P Phee for being willing to be my in-charge when A/P Sunita left NTU. I want to convey my heartfelt gratitude for the timely help he gave me.

I thank all my colleagues, past and present: Mr. Iwan (Project Officer), Mr. Robin (PhD student), Dr. Karali Patra (Research Assistant), Mr. Swandito (Research Assistant), Ms. Sinara Vijayan (Project Officer), Dr. Abhilash R.H. (PhD student), Dr. Safar Pour Abbas (PhD Student), Mr. Ahmed (PhD student), Mr. ShriShailesh (MSc Student), Ms. Vaishnavi (MSc Student), Mr. Venkat (MSc Student), Ms. Sudha (MSc Student) and Ms. Saranya (MSc Student) who have encouraged me through the years and also have been a good friend to me.

I would like to express my thankfulness to our lab technicians, Mr. Lim Eng Cheng, Mr. You Kim San and Ms. Agnes Tan for all the help they have done for me during my research. I would like to thank my confirmation report and thesis reviewers, Prof. Low Kin Huat, Assoc. Prof. Cheng I-Ming, Assoc. Prof. Michael Lau and Asst. Prof. Tegoeh Tjahjowidodo, for taking the time to evaluate and critique my work.

Lastly, I would like to express my indebtedness to my family, my wife and my friends for being great support throughout the time.

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LIST OF SYMBOLS

T_{rigid}	Transformation matrix in rigid image registration
α, β, γ	Angle of rotation about the x, y, z axes respectively
t	Translation vector along the x, y, z axes
$\langle . \rangle$	Expected value of ‘.’
$\Omega_{A,B}^T$	Overlap region between image A and B
$\bar{A}, \bar{B}$	Mean of the voxel value of image A and B respectively
$p(a), p(b)$	Probability density function of images (data volumes) A and B respectively
$p(a,b)$	Joint probability density function of voxel intensities in the overlapping domain of images A and B
K_p, K_i, K_d	PID controller gains:proportional, integral and derivative gains respectively
$y_M(t), y_P(t)$	Model and plant output respectively
$e_1(t)$	Error between $y_M(t)$ and $y_P(t)$
$u(t)$	Input to the plant
$k(t)$	Single adjustable parameter
$v(t)$	Measurable state variable
$A(x, y, z)$	Fixed reference frame for the end-effector
$B_t(x, y, z), B_w(x, y, z)$	Moving coordinate frame fixed at the transducer holder and water chamber
${}^A R_B$	Rotation matrix for the moving platform of the end-effector
p	Position vector of the centre of mass of the moving platform
ϑ_x, ϑ_y	Angle of rotation (euler angle) about the x axis and y axis of the B coordinate frames
d_i	Length of the i^{th} limb,
s_i	Unit vector along the length of the i^{th} limb
v_{bi}, v_p	Linear velocity at B_i , and p respectively

${}^B b_i$	Position vector of the joint on the moving platform for the i^{th} limb wrt coordinate frame B,
b_i	Position vector wrt A
w_p	Angular velocity of the moving platform/jig
v_{1i}, v_{2i}	Velocity of the cylinder and piston of the i^{th} limb
$\dot{v}_{bi}, \dot{v}_p, \dot{w}_p$	Linear velocity at B_i , P and angular velocity at P
J_p, J_{2i}	Manipulator Jacobian matrix and link Jacobian matrix respectively
F_p	Resultant and applied forces
f_e	External force acting at p
n_e	External moment acting at p
F_{1i}, F_{2i}	Resultant forces acting on the cylinder and piston of the i^{th} limb
m_p, m_{1i}, m_{2i}	Mass of the moving platform, cylinder and piston of the i^{th} limb respectively
$T_{1,2}, T_{3,4}$	Vector of input forces exerted at the actuated joints of limbs 1&2 and 3&4 respectively

LIST OF ABBREVIATIONS

CPD	Coherent Point Drift
CSF	Cerebro-Spinal Fluid
CT	Computer Tomography
DMRAC	Direct Model Reference Adaptive Controller
FUS	Focused Ultrasound Surgery
FUSBOT-NS	Focused Ultrasound Surgery Robot- Neurosurgery
GMM	Gaussian Mixture Model
HIFU	High Intensity Focused Ultrasound
ICP	Iterative Closest Point
IGS	Image-guided Surgery
LINAC	Linear Particle Accelerator
MIS	Minimally Invasive Surgery
MRI	Magnetic Resonance Imaging
NIS	Non-Invasive Surgery
PID	Proportional-Integral-Derivative
SRS	Stereotactic Radiosurgery
TPS-RPM	Thin Plate Spline- Robust Point Matching
US	Ultrasound

CHAPTER 1. INTRODUCTION

1.1 Background

Medical science has progressed leaps and bounds over the past three decades especially in the area of surgery. Open surgery requires long incisions on the patient's body which gives the surgeon direct access to the affected site, hence provides him/her live visual as well as tactile feedback during the surgical procedure. It also gives the surgeon a relatively unconstrained work area. However, the drawback of open surgery is the excessive loss of blood, long recovery time and scarring for the patient. Thanks to the advent of computer technology and robotics in medical field, nowadays Minimally Invasive Surgery (MIS) and Non-Invasive Surgery (NIS) methods are being used more frequently. In MIS, only a small access is made by the surgeon on the patient's body through which surgical instruments access the affected organ. In the case of NIS, no incision is made on the patient's body; the surgery is performed on the target using X-rays, Gamma rays, High Intensity Focused Ultrasound (HIFU) or other external sources. With MIS and NIS, the duration of surgeries has reduced considerably, there is reduced risk of infection and loss of blood, faster recovery and less scarring [1, 2].

Using Computer Aided Systems (CAS) such as the use of robotics and advanced imaging modalities, surgeons are now able to perform surgical procedures on micro scale, overcoming the limitations of humans like poor precision, repeatability and reliability. CAS allows for better visualization and targeting of sites as well as improved diagnostic capabilities, giving it a significant advantage over conventional techniques like open surgery where the surgeon requires direct vision to the target site or has to deal with issues like hand tremor. The use of robotics and its success in industry emboldened the idea of advancing robotic technology in the medical arena. There is great research interest in the field of biomedical robotics as the safety criteria for the application of these robots is very stringent. In order to ensure safety, the two main criteria for medical robots are accuracy and the response time. These criteria are partially met by real-time monitoring using imaging technology and its feedback to the robotic system. With the advancement of computing technology, imaging technology has greatly improved thereby giving better and accurate visual feedback to the surgeons in MIS and NIS procedures.

Another by-product of the computing technology is the ability to develop and implement highly complex and sophisticated control algorithms. Imaging technologies along with the control algorithms have led to the success of image-guided surgeries.

1.2 Problem Statement

In image guided neurosurgery, the pre-surgically obtained medical data such as CT, MRI, X-ray or Ultrasound images, are used to plan, simulate or guide the surgeon in performing tumour resection, biopsies or other surgical procedures. The surgeon, using these data, develops a pre-operative plan, which specifies how the tasks should be performed during surgery. The plan is developed in a co-ordinate system relative to the pre-operative image but the surgery is performed in a co-ordinate system relative to the patient's skull (in neurosurgery). Hence a transformation between the pre-operative data, plan and the patient has to be established. This enables any 3D point specified by the surgeon in the plan to be exactly located on/in the patient. This process is called surgical registration [3, 4].

One of the concerns in image-guided robotic neurosurgery is the tracking of the target tissue [5-10]. In the case of surgery on hard tissues such as bone structures, the movement of the target tissue can be limited to a great extent by clamps or other similar means. But in surgical procedures which deal with soft tissues, such as brain surgery, there are deformations which cannot be restricted or predicted [3, 10]. Also, neurosurgeries are performed over elongated operating time (6-7 hours), adding to the dislocation of the target [10]. In neurosurgeries, reliance on the pre-operative images for navigation would greatly deteriorate the accuracy of the procedure. This is true especially in neurosurgery as brain, being made of soft tissues, is known to undergo continuous and dynamic intra-operative deformations [10]. The deformations of the brain are unpredictable and vary in amount and pattern from surgery to surgery and from patient to patient. Deformations also varies from one part of the brain to the other [10].

Existing non-invasive neurosurgical robotic systems, like Cyberknife®[11], do not consider the target tissue deformations but only skeletal landmarks of the patient [12, 13], and assume a rigid relation between the skull and the tumour. They depend on external markers/fiducials

fixed on the head of the patient to track the tumour. This assumption may be true in the case of Cyberknife®, as it is a completely non-invasive system and it uses ionizing radiations like X-rays for destroying the brain tumours, which may not have immediate effect on its mechanical or physical characteristics. But this assumption fails in the case of a minimally invasive procedure or when modalities such as High Intensity Focused Ultrasound (HIFU) are used for tumour ablation.

The goal of this research is to devise a strategy to estimate this intra-operative deformation of the brain tissue and to compensate, in real-time, for this estimated deformation by orientating the neurosurgical robot so as to target the brain abnormality accurately. Figure 1.1 shows a general block diagram of a non-invasive neurosurgical robot. The main focus of this research will be on the imaging and image processing block of this diagram and also on the controller block. The developed controller will be tested on a representative robot which is highlight by the Robot block in the diagram. The aim is to develop techniques for real-time brain shift estimation and also to develop a control strategy for non-invasive/minimally invasive neurosurgical robots so as to accurately deliver treatment to the tracked brain abnormality.

Figure 1.1 General block diagram of a non-invasive neurosurgical robot

1.3 Image Control- Dynamic Deformation Estimation

Biomechanical modelling of the brain and intra-operative imaging are two of the methods used for tackling the problem of intra-operative brain shift. Various models for the brain deformation [9, 14-16] such as damped spring-mass model, continuum mechanics based brain model, linear hyper-viscoelastic constitutive model, models based on consolidation theory have been explored. The main drawback of estimation using models is that the precision and reliability is very low. This is due to the complexity and unpredictability of the phenomenon of brain shift. Many factors like loss of cerebro-spinal fluid, loss of cranial pressure, gravity, position of patient's head, use of anaesthetics and diuretics have been identified as the cause and as having influence on the amount and nature of the deformation and many factors are yet to be discovered [10, 16]. Accurate modelling of intra-operative deformation would be computationally expensive and time consuming. The use of biomechanical models of brain deformation along with the measurements of cortical surface deformation has also been investigated [16-20]. The main drawback of such methods is that the deformation of the subcortical structures of the brain cannot be predicted or measured based on what happens at the surface. These models seem to be good for surface shift prediction [10].

Intra-operative imaging [8, 21-23] is the other method by which the brain tissue deformation during surgery can be estimated. The intra-operative imaging is performed as frequent as possible so as to accurately track the deformations and update the pre-surgical images used for the treatment planning. The deformation is determined by registering the pre-operative images (MRI/CT) with the images taken during the surgery (MRI, CT, X-ray or ultrasound) or registering intra-operative images captured at different point of time during the course of the surgery.

The choice of imaging modality is a critical factor. For modalities such as MRI and CT imaging, the resolution and details of the images produced are of high quality. This provides the surgeon with adequate information about the current state of the target tissues. However, the image acquisition time is very high (approximately 60minutes) [10]. Also, integrating these modalities with other systems such as a robotic system would be expensive as the allied systems need to be MRI/CT compatible. X-rays images can be acquired really fast compared to MRI and CT

imaging but prolonged exposure to X-rays can be harmful to the patient. Ultrasound (US) imaging offers a good alternative to the aforementioned imaging modalities. US imaging is cost-effective, compact and portable and hence can be easily integrated with robotic system or other allied systems. US image acquisition is also very easy and fast and hence can be used for real-time monitoring of deformation [22]. However, the images have very poor resolution compared to MRI or CT images and also suffer from speckle noises and shadowing problem [24].

From the images captured using the intra-operative imaging modality, the extent of deformation is estimated with the help of image processing techniques like image registration. The choice of the image registration technique used to register the intra-operative images is also a crucial choice to make. There are many image registration algorithms developed [25] like rigid or non-rigid registration, point-based or intensity-based registration or use of different similarity measures like sum of square differences, minimising intensity differences, mutual information. For the estimation of brain deformation a non-rigid image registration algorithm is suitable as many studies have shown that brain shift is non-rigid in nature [5-10, 14-16, 18, 19, 26, 27]. Also the similarity metric used should also match the nature of the images. For example, in the case of ultrasound images using intensity based algorithm can be difficult as US images are known to suffer from intensity variations due to reflections and absorptions of the ultrasound beams [22-24].

Due to the unpredictability of the brain deformations and because biomechanical models are computationally intensive and time consuming, in this research, estimation of deformation using image processing technique on the intra-operative images is proposed. The imaging modality used in this work is ultrasound imaging and the image registration algorithm used is a non-rigid point-based image registration algorithm. A two-stage deformation tracking approach is proposed and implemented in this research. First, a coarse estimation of the position of the target is made using a fast and computationally simple template matching algorithm. This is followed by a finer estimation of the deformation with the help of Coherent Point Drift (CPD) non-rigid image registration algorithm. The estimation strategy was tested using brain phantom

with ultrasound imaging as the imaging modality. The average error observed in the template matching stage was 0.4mm with a computation time of approximately 0.8seconds and the non-rigid registration algorithm showed an average error of 1.94mm and an average computation time of 72.7seconds. By adding a down-sampling factor in the algorithm, the author was able to reduce the computation time by a factor of 5 to 9. However, the average error slightly increased to 2.18mm. This is an encouraging result both in terms of computation time and accuracy as the maximum deformation (worst case scenario) that was observed in various studies[8, 10] is 25-50mm at the end of resection of large tumours, which takes about 6-7hours in open surgery and the accuracy achieved by surgeons in open surgery is 3-5mm [27].

1.4 Robot Control- Hybrid Supervisory Control

Another important problem which is addressed by this research is the lack of a common control strategy for non-invasive neurosurgical robots. Today, each surgical robot has its customized control strategy. The availability of a generic control framework would result in faster development of robots as the researchers could concentrate more on optimizing the control scheme to realize its full capability for their particular application. This could also enable in formulating a common set of safety guidelines which every robot should adhere to.

The goal of this research is to devise a control strategy for non-invasive neurosurgical robots to dynamically track, target and ablate brain tumours. The two-stage deformation estimating algorithm tracks the tumour using real-time intra-operative images and the pre-operative images. The information about the deformations/dislocations of the brain tissues obtained through the tracking system assists the robot to track the change in the position of the pre-defined target and navigate the end-effector so as to target the abnormalities, under the supervision of a surgeon, without affecting the healthy tissues surrounding the target area.

In a minimally or non-invasive image-based neurosurgical robots, the robot is orientated based on the pre-planned trajectory which is updated in real-time by input from the intra-operative imaging. In other words, the robot operation is a look, plan and then move approach. Due to the deformation of the tissues during the surgery, it is possible that the target tissues will move closer to sensitive structures inside the brain or that the trajectory as per the treatment plan

would result in injury to surrounding tissues of the target. Hence, it is important that the robotic system plans and carefully verifies each step of the surgery, with the help of intra-operative imaging.

During surgery, neurosurgical robots are controlled and moved in such a manner that each and every point of the tumour volume is targeted without affecting the healthy tissues. The measurement of tissue deformation is made based on the image registration of the intra-operative images taken before and after each surgical manipulation. Based on the amount and direction of deformation obtained from the image processing, the pre-surgical treatment plan is updated. The trajectory of the robot is considered in two parts- coarse positioning (as per treatment plan) and fine positioning (compensating for tissue deformation).

Proportional-Integral-Derivative (PID) control is a widely used control method in the industry. It is simple, robust and easy to implement. But in situations where there is unpredictability, a PID controller alone may not be able to maintain good performance. The operating environment of a surgical is unpredictable due to the presence of non-linear disturbances and also there is a lack of knowledge of the complete system dynamics. The controller for a neurosurgical robot must be able to ensure high treatment delivery accuracy in the presence of such uncertainties. In order to exploit the simplicity of the PID controller and also ensure desired performance in the entire range of operating conditions, the best approach is to combine another controller which can perform well in the presence of uncertainties.

A hybrid supervisory controller combines two or more controllers in such a way that it can extract the advantages of the participating controllers and at the same time eliminate the disadvantages of the individual controller [28]. Hybrid controllers choose the controller to be used in the control loop with the help of a Supervisor. There are different types of Supervisors- pre-routed supervision and estimation-based supervision [29]. In the pre-routed supervision, each controller in the hybrid controller is switched into the control loop one after another in a predefined order till the required performance is achieved. This method is not useful when the number of controllers in the hybrid control is large. In the case of estimation-based supervision, the choice of the controller is based on the performance estimation for the given state of the

controlled system. When the performance of the controller in the loop becomes unacceptable, the best candidate controller from the other controllers in the hybrid structure is switched. This is a much more efficient method compared to the pre-routed supervision especially when the number of candidate controller is large.

In this work, a hierarchical hybrid supervisory control strategy is proposed as a generic control framework for neurosurgical robots independent of their geometry and configuration. A supervisor would decide which controller to use depending on the performance estimation of the controllers. PID controller and Direct Model Reference Adaptive Controller (DMRAC) were chosen as the parameterized controllers, along with an estimator-based supervisor for the proposed hybrid controller. PID control is considered the default controller in the developed hybrid controller. DMRAC is combined with PID control to form as hybrid controller so that the robot will be able to adapt to the changing environment. DMRAC does not require an explicit model of the plant to be controlled but only a model of the desired behaviour. The control scheme was devised in a hierarchical manner so that it breaks down the entire control problem into number of more tractable problems to increase computation efficiency. It also can enable the surgeon to act as the supervisor when required. In the case of an emergency due to failure of the robot or control software or in the event of takeover of the operation from the robot by the supervisor (surgeon), the exception handler must be able to handle the event safely and transfer the control to the surgeon. The schematic representation of the proposed control strategy (Image control and robot control) is shown in Figure 1.2.

The proposed hybrid controller was implemented and tested on a representative neurosurgical robot. HIFU-based non-invasive neurosurgical robot, **Focused Ultrasound Surgery RoBOT-NeuroSurgery** (FUSBOT-NS), which was developed by the Biomechatronics group in RRC, NTU, was modified as test bed for validation. The simulations and experimental testing of the proposed hybrid control architecture was performed for all range of motions in the robot's workspace and the positioning error was observed to be within desired range of 0.2mm. The expected accuracy was fixed based on the accuracy achieved in the deformation tracking stage and also based on the accuracy range achieved in the other neurosurgical robots [30, 31]. The

accuracy of the overall system was 16% better compared to the accuracy achieved using PID controller alone. The switching between the constituent controllers by the supervisor in the hybrid controller was done based on the error estimation and also on various events during the operation such as gross positioning of the end-effector and human operator intervention.

Figure 1.2 Schematic representation of the proposed control strategy for neurosurgical robots

1.5 Objectives

- To formulate and implement a common control strategy for the neurosurgical robots to accurately and dynamically target brain tumours according to pre-operative treatment plan which is updated based on intra-operative deformation estimation of the tumour;
- To implement a suitable strategy for dynamic image registration of the ultrasound images of the brain tumour during surgery;
- Experimental verification of the proposed scheme (as stated in 1 and 2 above) using a representative system.

1.6 Scope

- Control strategy for non-invasive neurosurgical robots to dynamically track and accurately target and ablate brain tumours. This involves the study of the dynamics of the system and that of the targeted tumour.
- Image registration techniques are studied so as to register the intra-operative brain tissue images to obtain the tumour position information required for targeting. The development and implementation of non-rigid image registration algorithm for dynamic tracking of deforming brain tissues also comes under the scope of this research.
- Biomechanical modelling of the brain is not considered in this work.
- As a part of development and implementation of the control strategy, various control methods such as PID control, adaptive control and hybrid supervisory controller are studied.

1.7 Overview

Chapter 1 gives a short introduction to this research project. The research problem and the proposed solution are described in brief in this chapter. The objectives, major contributions and scope of the work are stated and an overview of the report is provided.

Chapter 2 presents a literature review of the brain, brain tumours, and various treatment options and argues the case for the use of non-invasive HIFU-based image guided surgery. This chapter also discusses use of robotics in medicine and various image registration techniques.

Chapter 3 provides the detail discussion on the proposed strategy for the real-time estimation of brain tissue deformation. A two stage deformation tracking strategy, which uses template matching algorithm and coherent point drift algorithm for the dislocation estimation and deformation estimation respectively, is formulated and its role in the overall objective of this research project is discussed.

Chapter 4 details the proposed control strategy for the accurate positioning of the robot based on the input from the deformation tracker. A three-level hierarchical hybrid control architecture is proposed. PID controller and DMRAC are the constituent controllers in the

proposed hybrid supervisory controller. Each controller is formulated and the switching strategy of the hybrid controller is discussed in this chapter. The treatment protocols, Distant Point, Adjacent point and Arbitrary Point protocol, used for the HIFU-based treatment and the trajectory required for each protocol are also presented in this chapter.

Chapter 5 The testing of the proposed control strategy was conducted on a represented neurosurgical robot FUSBOT-NS end-effector. In this chapter, the end-effector design and its modification are discussed. The system kinematic and dynamic models are also presented and the workspace of the robot is discussed in this chapter.

Chapter 6 In this chapter, the testing of the dynamic deformation tracker and the hybrid control strategy proposed and implemented in this work are presented and discussed. The experimental setup and the test results of the two-stage dynamic brain tissue deformation tracking strategy using template matching algorithm and coherent point drift algorithm are presented and discussed in this chapter. The simulation, implementation and error analysis of the hierarchical control strategy are also presented and discussed. The integrated robotic system is tested and validated and the results are discussed.

Chapter 7 concludes the research work done in this project. The future directions for this research project are discussed and the major contributions made by the author described.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

The study of brain tumours and various methods to treat it is an extremely important field of research. It may not be one of the top ten causes for cancer but statistically, it is the leading cause of solid tumour cancer in children below the age of 19 and the second leading cause of cancer deaths in young adults (20-39years). Brain tumours are also the second fastest growing cause of cancer deaths in people of age over 65 [32].

It is extremely difficult to treat brain tumours because of their location i.e., inside the brain, which is the control centre for all our thoughts and action, and can severely compromise the quality of life of the patient if healthy tissues are injured during treatment. There are about 120 different types of brain tumours making the treatment even more difficult [32]. The complexity of the brain anatomy together with the uncertainty of the tumour growth makes the conventional invasive surgery an extremely challenging task for the neurosurgeons. Prevention of brain tumours is not possible as little is known about their cause(s) [33].

Hence, it is important to investigate non-invasive, less complicated and more effective ways for treating brain tumours. Some of such alternatives that have been researched are radiation therapy including standard external beam radiotherapy, chemotherapy, stereotactic radiosurgery like Gamma Knife and Cyberknife.

2.2 Brain

The central nervous system consists of the brain and spinal cord immersed in the cerebrospinal fluid. The brain consists of three main parts: cerebrum, cerebellum and the brainstem[32, 34].

Cerebrum

Cerebrum is the largest part of the brain. It is divided into two hemispheres with each hemisphere controlling the opposite side of the body [32, 34]. It consists of the frontal, temporal, parietal and the occipital lobes. Its functions are related to conscious thought, movement and sensation.

The outer layer of the brain is known as the cerebral cortex or the 'grey matter' which is formed by closely packed neuron cell bodies. The grey matter includes parts of the brain which are concerned with muscle control, memory, sensory perceptions, emotions and speech [34].

The nuclei deep within the cerebrum, which is covered by the grey matter is known as the white matter [34]. White matter are neuronal tissues containing mainly of long myelinated axons. They are involved in the transfer of sensory information from the rest of the body to the cerebral cortex, regulation of involuntary functions such as blood temperature, heart rate and blood pressure and also certain nuclei within the white matter are involved in the expression of emotions, release of hormones and regulation of food and water intake.

Figure 2.1 Brain anatomy [34]

Cerebellum

Cerebellum is the second largest structure in the brain [32] and is made up of two hemispheres. It is located at the lower back of the head. The cerebellum co-ordinates sensory input from the inner ear and the muscles to provide accurate control for walking, balance, posture and general motor co-ordination.

Brainstem

The brainstem forms the link between the cerebral cortex, white matter and the spinal cord. It is situated at the base of the brain. It helps in the control of breathing, sleep and circulation [34].

2.3 Brain Tumours

There are more than 120 different types of brain tumours. Many of the tumours have different subtypes. Tumours are generally assigned grades ranging from Grade I (least malignant) to Grade IV (most malignant) [32]. Grade I tumours grow slowly and are usually localised to one part of the brain while Grade IV tumours grow quickly and invade the surrounding part of the brain or body. Surgical treatment of benign tumours is just as difficult to treat as malignant ones [35].

Symptoms of brain tumour depend on the tumour size and location. Vomiting, nausea, irritability and headaches are some of the common symptoms. In some cases seizures, personality changes, weakness are also symptoms.

Brain tumours are broadly classified as primary and secondary tumours [32]. Primary tumours can be malignant or benign. They rarely spread beyond the central nervous system. Secondary tumours on the other hand are originated at some other part of the body and later spread to the brain. They are also called metastatic tumours.

The most common types of brain tumours and their percentage of occurrences are shown in Figure 2.2. A brief description on the most common brain tumours are given below [32]:

Astrocytoma

Gliomas account for 42% of all the tumours and 77% of the malignant ones [32]. Astrocytomas are the most common type of glioma. They are formed on the supporting cells of the brain which are the star-shaped glial cells [34] called the astrocytes. Astrocytomas are also graded from I to IV. In children, most of the cases are considered low-grade while that in adults as high-grade.

Figure 2.2 Occurrences of different brain tumours [32]

Medulloblastoma

Medulloblastoma arise in the cerebellum. They account for 25% of all the childhood tumours [32]. They are aggressive and invasive and spread throughout the central nervous system through the spinal fluid.

Meningiomas

Approximately 29% of the brain tumour are Meningiomas [32]. They are formed from the thin, protective membrane that covers the brain and spinal cord called the meninges [32, 34]. They affect people of all ages but mainly those in the forties esp. women. They are slow growing tumour and do not spread to the neighbouring normal healthy tissues. Majority of the tumours are benign but they can recur.

Pituitary tumours

They account for 6% of all the tumours [32]. They arise from the pituitary gland which is situated at the base of the brain. They are almost always slow growing, non-malignant and curable. They can occur at all ages. There are two types of pituitary adenomas 1) non-secreting

and 2) secreting. The non-secreting tumours occur mostly in middle-aged people and the elderly while the other occurs in young adults. The secreting type tumour can cause high levels of pituitary hormones in the body, which can affect other parts of the body.

Metastatic Brain Tumours

Metastatic or secondary tumours originate as cancer cells in another part of the body and then metastasize through blood or spinal fluid to other parts. While lung, breast, colon, melanoma, and kidney cancer pose the greatest risk, brain metastases have been associated with many other cancers. Secondary brain tumours can reappear years after the primary tumour has been diagnosed and treated. The highest incidence of the metastatic brain tumour is in people over the age of 65 [32].

2.4 Various Treatment Options

The treatment method is adopted based on the type and location of the tumour, the patient's general health, medical history and preference. Treatment options can be classified into invasive, minimally invasive and non-invasive methods.

A. Invasive treatment

Surgery

This is usually the first line of treatment. The main objective of the surgery is to remove as many visible tumours as possible with minimum damage to the intervening healthy tissues. Surgery helps in relieving the intracranial pressure build up in the skull due to the tumour growth. Craniotomy is the most common type of surgery and it involves making a small opening in the skull by removal of bone and the dura mater so that the tumour site can be accessed. After the surgery the bone is replaced. Craniotomy is done not only for tumour resection but also for biopsies. After the surgery the treatment is usually followed up by radiation or chemotherapy.

Interstitial brachytherapy

In this method, radioactive seeds are placed directly into the tumour and are kept there for a certain period of time (See Figure 2.3). This procedure has been mostly replaced by stereotactic radiosurgery which is a non-invasive treatment.

Invasive treatment has the risks and complications associated with bleeding, infections, brain edema, seizures, paralysis, behavioural and cognitive changes. The chances of damage to normal tissues are high and these injuries can lead to permanent impairment associated with those injured areas.

Figure 2.3 Radioactive wafer being placed in the resection cavity [36]

B. Minimally invasive treatment

Stereotactic radiosurgery (SRS)

Unlike in the case of conventional radiotherapy, SRS delivers high dose of radiation (2-30Gy) in a one-day session. In certain SRS procedure, a head frame is attached to the skull (for example, in Gamma knife) before taking CT or MRI scan [31, 37]. With the aid of computer imaging, the accurate location of the tumour is calculated and the radiation is beamed directly to the tumour, often from several different directions. In newer SRS methods head frames are not used (for example, in Cyberknife [38]). Figure 2.4 shows Gamma knife and Cyberknife stereotactic radiosurgery system.

The advantage of SRS is their precision and so surrounding tissues that are affected by the radiation is less. The dosages can also be fractionated. The disadvantage is that the radiation used in these modalities i.e., Gamma rays, X rays and so on are ionizing radiation and hence can alter the DNA of not only the tumour tissues but also that of the irradiated healthy tissues. This can lead to lots of temporary as well as permanent side effects such as memory loss, loss of appetite, fatigue and skin reactions (rash, redness, hair loss). Sometimes the dead tumour cells can form a mass (radiation necrosis) and cause the same symptoms as tumours.

Figure 2.4 Stereotactic surgical systems (a) Gamma Knife system [39] (b) Cyberknife system [11]

The term stereotaxis, derived from the Greek stereo- for “three dimensional” and –taxis for “an arrangement” was coined by Horsley and Clarke in 1908. It was their use of a three-dimensional Cartesian coordinate system that gave the foundation for all stereotactic system used in modern neurosurgery [31]. Stereotactic radiosurgery(SRS) would be one of the most preferred methods compared to the other modes of treatment as 1) it is non-invasive 2) it causes the least damage to the tissues or parts of the body other than the tumour itself.

In SRS, before the treatment the location of the tumour is determined with the aid of imaging modalities such as MRI/CT. This helps in accurately placing the radiation dose on the tumour. Since this is a non-invasive treatment, the location of the tumour is monitored and updated during the surgery by taking images of the tumour intra-operatively. Some of the commonly used intra-operative imaging modalities are MRI, CT, X-ray or ultrasound imaging.

There are three underlying principles in the functioning of all stereotactic systems [36]

- 1) Defining a co-ordinate system for the imaging modality and also for the surgical field.

The pre-operative images such MRI or CT images are 3-D images that have details of the intracranial structure of surgical interest. The imaging parameters such voxel dimensions, inter slice spacing and slice thickness are all stored by the scanner device. These parameters would define the image co-ordinate system or the image space.

The surgical field is the co-ordinate system of the robotic system or mechanical arm employed which holds the medical tool for performing the surgery.

- 2) Determining the spatial relation between these two co-ordinate systems.

As was discussed earlier, there are two types of SRS: frame-based and frameless surgery. In the case of frame-based surgery, the pre-operative image is taken with the frame rigidly attached to the skull. So the frame base appears in both coordinate systems and hence the relation between the image space and the surgical space is known.

But in the case of frameless surgery, the two coordinate systems do not have any mutual relationship initially. With the use of image processing techniques patient-to-image registration is done. This procedure finds the transformation matrix describing the transformation from a single coordinate in the surgical space to the corresponding coordinate in the image space.

- 3) Presenting the resulting information.

During the surgery, the image guidance information should be presented to the surgeon.

Frame-based procedures

Frame-based surgery involves rigid application of the stereotactic frame to the skull, prior to taking the pre-operative images and the subsequent surgery. The frame is secured to the skull often by screws and then is attached to an immobilization mechanism. The stereotactic frames have high contrast image markers so they appear on the images. Since the frame appears in the pre-operative images, and because the frame is fixed rigidly to the skull, the internal structure

of the brain can be correlated to the head frame, which acts as reference. With a fixed relationship between the patient's head and the frame, any intracranial target can be reached with an optimal trajectory and great accuracy. The standard performance specifications for cerebral stereotactic systems, specified by the American Society for Testing and Materials, stipulate a mechanical accuracy of 1mm [31].

Within the Cartesian coordinate system, the x-axis refers to the medial-lateral location, the y-axis the anterior-posterior location, and the z-axis refers to the base-vertex location [31]. Though there are many proposed methods for determining the z-axis, the most popular one is the use of posts with a "N" shape configuration. The position of the inclined rod relative to the vertical ones determines the z plane of the slice.

The Leksell Frame

The Leksell Frame was developed by Dr. Lars Leksell, a Swedish physician and Professor of Neurosurgery in 1951 at Karolinska Institute, Stockholm, Sweden. The Leksell frame is shown in Figure 2.5. Essentially it consists of a semi-circular arc with a movable probe carrier. The arc system would be attached to the skull of the patient with pins such that the centre of the arc would be at the selected target. Rotation of the arc around the axis rods in association with the lateral adjustment of the electrode carrier helps in choosing any convenient entrance point irrespective of the location of the target [31].

The radius of the arc is 190mm and the stereotactic designated in the Cartesian coordinate system with centre established at $x=y=z=100\text{mm}$ and the zero, by convention, at the right, posterior and superior [37]. Therefore, the probes attached to the probe carrier can have a working space of 190mm to access the target. The coordinate of the target can be confirmed by a lateral X-ray through the Z rings, the tip of the probe terminating at their centre [31]. For stereotactic surgery, the arc allows for any entry point above the head ring as the arc can be moved in the x, y and z directions. The frame is CT and MRI compatible as it is made of titanium and also there is no phantom frame with this system [37].

Figure 2.5 Leksell Frame with Z rings and arc attached to the base frame [31]

A variety of medical tools are available to attach to the probe carrier like twist drill, which is widely used, biopsy systems, hematoma evacuation kits and lesion generating devices are available. Other accessories for microsurgery are also available. A software program which simulates the probe trajectories, called SurgiPlan, is also available [31].

BRW/CRW Frames

The Brown-Roberts-Wells system was developed at the University of Utah in 1977 by Theodore Roberts and a third year medical student, Russel Brown. This system, originally a CT-based system, consists of a skull base ring and carbon epoxy head posts. The skull base ring is fixed to the skull of the patient using screws. The localizer unit is secured to the ring and consists of six vertical posts and three diagonal posts which have an N-shaped configuration. This N-shaped construct helps in establishing the axial CT plane with respect to the skull base, by determining the relative distance of the oblique to the vertical rods. The coordinates of each of the nine fiducial rods and that of the target are determined on the CT/MRI monitor. The BRW frame also includes an arc and a probe carrier. This arc is capable of four motions which create infinite possibilities for reaching the target. But for any pathway, the computation must include the entry coordinates. The accuracy of the setting can be tested on a phantom base which is provided along with the system [37].

The design of the frame was improved and simplified in 1980s by Wells and Cosman and was made similar to the Leksell frame. The arc system of CRW frames directed the probe isocentrically around the designated target location. Some of the BRW frame designs were retained in this like the phantom frame, CT localizer and the same probe depth which is, 160mm. Some of the latest innovations include MRI compatible frames and localizer, and adeptness in arc-to-frame applications [37].

Frameless procedures

Frameless surgery, unlike the frame-based surgery, do not use frame that is rigidly fixed to the patient's head. With advancement and improvement in the imaging technologies, such as CT and MRI in the recent years, pre-operative visualisation of the intracranial anatomy of brain has improved considerably which in turn aids neurosurgical planning. But this pre-operative image needs to be related to the actual surgical field for the accurate localisation of the target. Previously this, correlation of the pre-operative images with the surgical field, used to be visualised mentally by the surgeon which is an extremely challenging task when dealing with complex structures like that of the brain. To tackle this problem and to avoid the need for a head frame, various techniques have been developed to perform 3D digitisation of the surgical space.

Image processing methods must be employed to correlate the image space and the surgical space. For doing this, there are basically two approaches 1) point-pair matching 2) surface matching. These two are discussed later in the chapter under image registration algorithms. In the case of frame-based procedures, the head acted as the reference in both the image and the surgical field. Similarly in order to have some reference in both the image and surgical field, surgeons, in some cases, fix point markers on the body of the patient before the image acquisitions. These markers are also called fiducials.

Fiducial markers are gold seeds or stainless steel screws that are implanted in and/or around a soft tissue tumour, or within the bony spine to act as radiologic landmarks [40]. They are placed using CT or image-guided percutaneous methods or endoscopic or surgical methods. The

fiducial must be fixed with respect to other fiducials and the tumour to ensure accurate targeting.

Some of the key fiducial placement principles are 1) implant 3-6 fiducials with 2cm. spacing between fiducials. 2) There must be 15 degrees angle between any grouping of 3 fiducials and not collinear and encompassing the tumour.

Any fiducial migration will degrade the accuracy of the image-guidance system and this happens especially in the case of soft tissues.

Radio Frequency Ablation

This is one of the upcoming brain tumour ablation techniques. It is a minimally invasive procedure where radio frequency (RF) electrodes are inserted into the tumour and high frequency alternating currents are passed through one electrode through the surrounding tissues into the 'indifferent' electrode [41]. The ionic agitation due to this current flow results in frictional heating and when the temperature rises above 70°C coagulative necrosis develops in the tissue.

C. Non-Invasive treatment

Radiation Therapy

High energy radiations such X-rays or other ionizing rays are used to stop or reduce the growth of tumours which are inoperable. It is also used to destroy residual tumours after surgery or delay the tumour recurrence. Ionizing radiation mutates or alters the DNA of the affected cells. Thus over time, the tumour cells are destroyed.

Radiation therapy is done either using external beam or other interstitial methods (e.g. interstitial brachytherapy).

The external beam method involves machines like linear accelerators or cobalt machines. They target the tumour cells from outside the body. In the conventional radiation therapy the beam is focussed at an entire region of the brain where the tumour is located. The radiation therapy

is usually fractionated and given over a period of time in doses of 1.8-2 Gy (Gy stands for *Gray*. One *Gray* is the absorption of one joule of energy, in the form of ionizing radiation, by one kilogram of matter). The radiation may be focused at the tumour and the surrounding areas or the whole brain. Whole Brain Radiation Therapy (WBRT) is used to treat multiple tumours and metastatic tumours.

Chemotherapy

Chemotherapy is the treatment method by which drugs, that have toxic effect on the tumour cells, are delivered to the patient. They are delivered either orally or through injection. But the Blood Brain Barrier (BBB) can prevent drugs from reaching the brain. So BBB disruption is done to disrupt the barrier temporarily and allow the drugs to reach the tumour. Chemotherapy is usually a secondary treatment or is used to delay or replace radiation treatment in children. Certain types of tumour do not respond to this treatment and also the overall health of the patient must be good enough to withstand the side effects of the treatment.

Chemotherapy has a lot of side effect to it. The drug enters and affects other parts of the patient's body too. It can affect the bone marrow and cause low production of the blood cells (myelo-suppression), it can cause low white blood cell count (leukopenia), affect the digestive system, weaken the immune system and many other complications.

High Intensity Focused Ultrasound (HIFU)

HIFU is a non-invasive surgical modality that is increasingly being used in recent years, particularly in the field of urology and oncology [2]. HIFU surgery is based on the thermal effects of ultrasound and is useful when the dosage is well controlled and delivered at desired spot. The dosage has to be planned for each specific case by considering all the exposure parameters before the actual surgery.

Unlike the surface heating or freezing effect of laser surgery and cryosurgery, HIFU can induce lesions deep in the tissue, without affecting the intervening tissues, by focusing the beam at the desired location [42]. The tissue is rapidly heated to temperatures between 65 and 100°C at

the focus of the beam, causing irreversible cell damage and thermal coagulative necrosis. The ablative thermal energy is usually deposited within 5 – 20seconds [43].

The action of HIFU on tissue causes thermal and non-thermal effects (cavitation, oscillatory motion and acoustic streaming). Acoustic cavitation is the process of formation of bubbles that acutely increase in size at the point of resonance, and when the bubbles suddenly collapse, it results in very high pressure (20,000 to 30,000 bars) thereby damaging the nearby cells. Though the result is cell necrosis itself, it has not been used for tissue ablation yet as cavitation is a complex and unpredictable process. Efforts are being made to control cavitation as a combination of cavitation and thermal effect would help in creating lesions faster and deeper [44]. The biological effects of HIFU on tissue vary based on the properties of the target tissue and the parameters of the HIFU operation [45]. By changing the intensity and exposure time of the HIFU beam, we can change the effect it has on a given tissue. An important parameter during HIFU treatment is Dose. Dose (J/cm^2) is defined as the product of the intensity (W/cm^2) and the exposure time (seconds) of the HIFU beam. Similarly, different absorption coefficient of the different tissues leads to different biological effect during HIFU operation. The absorption coefficient is depended on the frequency of the beam. Higher frequency results in greater absorption of acoustic energy in the tissues which means a lower HIFU dose would be required for the desired effect. Also the focal region of a beam becomes smaller with increase in frequency [45].

The lesion is typically a cigar-shaped three dimensional zone with its long axis perpendicular to the axis of propagation. There is a steep temperature gradient between the focus and the neighbouring tissues, which is showed by a sharp demarcation between the volume of necrotic tissues and the surrounding cells on histologic examination. The dimension of the lesion depends on the frequency and the geometry of the source. The dimension of the lesions is usually of the order 10 – 50mm in length and 1 – 5mm in diameter [43]. Figure 2.6 shows the lesion created in the brain of a dog. The focal region is very small that, for ablating a large volume of tissue, the focal zone is shifted sequentially by incremental movement of the transducer along with adjustment of the focal length.

Figure 2.6 Lesion in white and grey matter of a dog shown in the black box [46]

Ultrasound waves are generated by high frequency vibration of a piezoelectric or piezoceramic transducer. They are brought into a tight focus by a spherically arranged acoustic lens or parabolic reflectors [43]. Since ultrasound waves do not travel through air, they are coupled by degassed water between the source and the tissue.

An important factor in clinical application of HIFU is the ability to accurately monitor the treatment. This is achieved using real-time ultrasound [47-49] or MRI imaging [50]. One of the common side effects of treating with HIFU is skin burn. They occur due to the absorption of ultrasound energy at the interface between two materials that have different attenuation properties. The greatest clinically relevant absorption occurs at the skin level [43].

The application of HIFU therapy for neurological disorders has generated lots of interest in the research community. Lots of research [45, 46, 51] has been going on this area for the last 5 decades but the success rate has been quite low. But due to much improved imaging

technology and control strategies it has emerged as a promising area of ultrasound research. Various treatment possibilities such as suppression/stimulation of nerves, healing of peripheral nerves, ablation of brain tumours and opening of blood-brain barrier, are being explored by several research groups [45].

Ultrasound gets highly attenuated by air and skull. Due to this property of ultrasound, it is very difficult to destroy a tumour inside the brain without craniotomy. Usually a small opening of about 10mm diameter is made in the skull to act as the acoustic window for the HIFU beam path. This is a minimally invasive procedure rather than an invasive one as the dura mater kept intact and only a portion of the skull is removed. Hence the procedure is non-invasive to the brain.

Many research groups are investigating the transcranial application of HIFU [45]. But transcranial HIFU application suffers many drawbacks primarily due to the in-homogeneity of the skull, the phase and amplitude distortion of the HIFU beam due to high attenuation of the skull and defocusing of the beam [45]. Transcranial HIFU application can cause excessive heating of the skull and also reverberations. Hynynen et al and M. Fink et al [45, 52, 53] have demonstrated effective focusing in the transcranial application using phased array. Though the use of phased arrays has showed encouraging results, there are still drawbacks such as skin burns [45].

Other Non-invasive treatment methods

- 1) Immunotherapy, where immune system of the patient's body is made more effective to find and destroy cancer cells
- 2) Gene therapy, where the attempt is to repair the genes of the abnormal cells with cause the cancer.
- 3) Angiogenesis Inhibitors are drugs which interfere with the growth of blood vessels. The tumours cannot grow without these blood vessels with provides it with nourishment.

The conventional surgical methods for deep-seated tumours or other abnormalities in the brain require large incisions to reach the site. This can lead to heavy blood loss and other complications during the surgery as well as after the procedure. Also the patient would require long recovery time which leads to high hospitalisation cost. Non-invasive or Minimally invasive mode of treatment is always preferred. Some of the reasons for the choice are

- 1) No or very little loss of blood.
- 2) Usually less trauma to the tissues.
- 3) Less recovery time. The treatment can be given on an out-patient basis.
- 4) Smaller surgical scar(s).
- 5) Less need for pain medication.

2.5 Robotic System Overview

The Robotic Institute of America (R.I.A.) defines a robot as, “A re-programmable multi-functional manipulator designed to move materials, parts, tools, or specialized devices through variable programmed motions for the performance of a variety of tasks” [54]. The word ‘robot’ was first coined by the playwright Karel Capek in this satirical drama *Rossum’s Universal Robots*. He derived the word from the Czech word *robota* which means slave labour [55]. Development in robotics was mostly fuelled by the need to manipulate and handle hazardous materials such as radioactive or poisonous materials. Remote manipulators or teleoperating systems began to emerge in the 1940s [55] and since then, robots have been used in industry for different applications from arc welding to assembling electronic devices which traditionally were performed by humans. The technology developed was later used in many other areas like agriculture, space exploration and surgery as robots have good repeatability, accuracy, ability to work in hazardous environments and do not experience fatigue. Nevertheless, robots have their own drawbacks such as high cost, less dexterity compared to humans and inability to process qualitative information [55].

There are a large variety of robots available in the market but not all can be used for all applications. The selection is made based on certain characteristics of the robot. There are a number of characteristics by which we can assess the capability of a robot. Some of important ones among them are [54-57]:

1) Repeatability, Precision and Accuracy: Repeatability is the ability of a robot to reach the same tool position repeatedly. The robot may not reach the exact position each and every time but will be within a certain range from the desired location. There will always be some repeatability error due to flexibility of links or backlash of gears.

Precision of a robot is the measure of the spatial resolution with which the tool can be positioned within the work envelope and accuracy is a measure of the ability of the robot to position the tool at any arbitrarily set point in the workspace.

2) Degrees of Freedom: It is the number of independent motions that the robot can perform. It is defined by the number of rotational and translational axes through which the robot can move. The number of degrees is significant because it describes how constrained the motion at the end-effector of the instrument will be.

3) Work envelope and Resolution: Work envelope or work space is the space in which the end-effector of the robot can reach and/or work. The size and shape of the workspace depends on the configuration of the robot arm, and also on its DOF. Resolution is the smallest incremental movement it can make or measure.

4) Dynamic range: It is defined as the ratio of the highest and lowest force that the robot can exert. This is important to know because a robot with a high dynamic range, similar to the human range, is difficult to design. This is particularly important in surgical intervention where in some portion high forces are required (as in bone drilling) while in some other portion of the surgery very low forces are required (as in suturing).

5) Control system: It is one of the most important characteristics of a robot which determines its performance. It defines the method which is used for controlling the different axes of the robot. It is a very crucial part of medical robots because of the stringent safety requirements.

The control system of a robot enables to plan and execute motion accurately and also in case of failure, it helps in failing in a predictable manner.

2.6 Robotics in Medical Application

Nowadays robots have been widely used in the medical field especially in surgery. The robotic system used for surgery are computer-integrated systems and the robot itself is just one element of a larger system designed to assist a surgeon in carrying out a surgical procedure that may include pre-operative planning, intra-operative registration to pre-surgical plans, use of a combination of robot-assisted and manually controlled tools, and postoperative verification and follow-up [58]. Robotic systems eliminate some of the human weaknesses, such as fatigue, poor repeatability, tremor, that limit the efficiency of the surgeon to perform his/her task. But at the same time, robotic systems lack the versatility and dexterity of humans, they lack the ability to process qualitative information, they are expensive and cumbersome and large [55]. Table 2.1 compares the advantages and disadvantages between a human surgeon and a surgical robot.

Besides the wide range of medical robotic systems already available in the market, lots of research and development are being carried out to develop new methods and applications. Initially the attempt of researchers was to adopt industrial robots for medical applications with some modification. The robot for joint replacement surgery, ROBODOC, was derived from an industrial robot configuration such as SCARA [59, 60].

Surgery

Surgery is a medical procedure which involves physical intervention on tissues. As a general rule it is a procedure in which incisions are made on the human body or closure of a previously sustained wound. Depending on the size of the incision made, surgery can be classified as:

Open surgery

It is a conventional mode of surgery where large incisions (more than 5cm) are made so that the surgeon can easily access the structure or organ involved. Here the surgery is performed by

the surgeon and the role of robotic systems is limited to intra-operative scanning or other related tasks which do not involve any tissue manipulations [60].

Table 2.1 Advantages and disadvantages of robot compared to humans [55]

	Surgeons	Robots
Advantages	Task versatility	Repeatability
	Judgement experience	Stability and accuracy
	Hand-eye coordination	Tolerant of ionizing radiation
	Dexterity at mm-to-cm scale	Diverse sensors
	Many sensors with seamless data fusion	Optimized for particular environment
	Quickly process extensive and diverse qualitative information	Spatial hand-eye transformations handled with ease
		Manage multiple simultaneous tasks
Disadvantages	Tremors	Expensive
	Fatigue	Cumbersome
	Imprecision	Large
	Variability in skill, age, state of mind	Inability to process quantitative information
	Inability to process quantitative information easily	Not versatile
	Ineffective at submillimetre scale	Technology still in infancy

Minimally Invasive surgery (MIS)

Minimally Invasive Surgery was established as a surgical technique in the 1980's. In contrast to traditional surgery, MIS is carried out through very small incisions using long instruments and cameras. Generally, a set of three to five incisions of 1cm diameter are made through which the surgeon accesses the target site with the help of specialised equipments. The surgeon views the target using cameras which are handled via tubes which are inserted into the body through the small incisions made.

Minimally invasive surgeries have lots of advantages compared to the open type with less recovery time, less loss of blood, less trauma for the patient and less scarring. Yet, MIS has a different set of challenges [61-63]

- 1) Loss of degrees of freedom due to the limitation of performance of a task in a confined space and the range of motion of instruments is restricted.
- 2) For laparoscopic techniques, 3-dimensional imaging is lost on a 2-dimensional television screen.
- 3) Loss of tactile feedback and depth sense.
- 4) Training required for the surgeon since they need to do mental transformation as the endoscopes orientation is different from that seen on the screen.

Most problems of MIS mentioned above can be solved with the help of good robotic manipulator design with force sensors for tactile feedback and better imaging technique for better vision. There are widely used MIS systems around the world like Da Vinci Prostatectomy which is shown in Figure 2.7.

Figure 2.7 da Vinci Prostatectomy [17] (a) Incisions made in open surgery and MIS case, (b) da Vinci Prostatectomy system

Non Invasive Therapy and Surgery

In this mode of surgery, no incision is made on the body of the patient. Here the tumours or the cancerous tissues are destroyed by radiation like X-ray, Gamma rays or High Intensity Focused Ultrasound (HIFU). The advantages of this are similar to that of MIS and these systems are increasingly becoming popular in the medical field. In order to destroy the tumour beneath the skin, accurate tracking and targeting of the tissue is required for which a robotic system is needed. With improvement in imaging technologies, viewing and visualising deep-seated

tissues have become possible [55]. MRI and CT are the preferred pre-operative imaging modalities and ultrasound and X-ray are used intra-operatively. With the help of these images, the robot is able to accurately locate and target the tumour during surgery.

2.7 Robotic systems in Neurosurgery

Though robotic systems are not yet reliable enough to autonomously perform a complete surgery, they are very useful and act as an enhancement to the surgeons arm in the operating room. They aid in performing relatively straight forward procedures like intra-operative scanning as well as complicated surgical procedures with considerable human input and guidance. The Da Vinci Surgical System is an example of one such system [55, 64]. Some examples of neurosurgical robots systems available in the market and research centres are described below. A table which summarises the function, mechanical configuration, mode of control and accuracy is presented in Table 2.2.

1) Automated Positioning System (APS) - This robotic system is developed by Elekta, Stockholm, Sweden. It is a particular upgrade to the Leksell Gamma Knife radiosurgical system and is one of the simplest and most widely used supervisory controlled robots. Based on the treatment plan, the APS will adjust the patient's head within a collimator automatically. The advantages of using APS are: faster treatment, lower shuttle dose, more number of shots in the critical regions is possible and it eliminates the chances of human error due to manual adjustments [65, 66].

2) NeuroMate- It is an image-guided robotic system developed by Integrated Surgical System, Inc., U.S.A. for stereotactic needle placement. It uses anatomical landmarks for manual registration. The function of the NeuroMate is to determine the accurate location for the insertion of a drill, probe or electrode based on the pre-operative images [8]. The robot is not powered when the probe is entering the surgical field but passively constrains the surgeons [8].

3) Neurobot- It is a special purpose telerobotic surgical system developed as a part of European Community funded project for neurosurgery [3]. It has been successfully used in complex procedures requiring simultaneous retraction and dissection [66]. The intra-operative target

location is tracked in real-time using ultrasound imaging so as to compensate for the brain shift [66].

4) Cyberknife– Cyberknife is an image-guided robotic radiosurgery system developed by Accuray (Sunnyvale, CA) (See Figure 2.8). It is capable of delivering highly precise cross fired radiation beams that yield a conformal radiation dose distribution with sharp fall in dosage at the perimeter of the target lesion. It uses near real-time X-ray imaging to achieve accurate target localisation and high-speed robotics for accurate dosage delivery [38]. The treatment process begins with pre-operative CT images of the tumour that are input to a path planning algorithm that generates the spatial path for the linear accelerator carried on the robot. At procedure time, it automatically registers the pre-operative path by correlating real-time radiographic images with the pre-operative CT images to locate and eliminate the tumour in the patient. Before the treatment, the treatment plan are reviewed and corrected by the surgeons. However, during the surgery, Cyberknife operates completely autonomous [55].

Figure 2.8 Cyberknife system [11]

5) Evolution 1- The robotic system is developed by Universal Robot Systems, Schwerin, Germany. The system has been successfully tested for several neurosurgical applications like pedicle screw placements and endoscope-assisted transphenoidal pituitary adenoma resections. However surgeons who have performed these procedures using the system have found it too cumbersome and time consuming to justify its use [66].

6) Minerva- Minerva was developed at the University of Lausanne, Lausanne, Switzerland for stereotactic biopsies or functional neurosurgical applications [66, 67]. The project attempted to

account for the brain deformation with the help of CT scanner to provide real-time image guidance. Here, the robotic arm, which is placed inside the CT scanner, moves to the specified site in a pre-programmed trajectory defined by the integrated neuronavigation systems. The project was discontinued due to safety issues [66].

7) NeuRobot- NeuRobot is developed by Shinshu University School of Medicine, Japan. It is a telecontrolled master-slave micromanipulator system used for neuroendoscopy [68]. The micromanipulator is a tubular cylinder of 10mm diameter with three 1mm diameter microinstruments with three DOF placed inside it. The surgeon controls the microinstruments using three levers on the operation-input device while watching a 3D monitor. Microinstruments such as micro-forceps, micro-hooks, micro-needle and laser tips can be used as surgical tools. They can be exchanged during surgery as well.

Table 2.2 Various neurosurgical robots, mode of operation, functions, accuracy and mechanical configuration

Name	Company	Operation	Function	Accuracy	Mech Config
Cyberknife	Accuray Inc.	Supervisory control	Radiosurgery (LINAC)	1.1±0.3mm	serial
Neuromate	Renishaw	Supervisory control	Biopsies	0.86±0.32mm (frame based) 1.95±0.44mm (frameless)	serial
NeuRobot	Shinshu Univ. School of Medicine	Telesurgical	Endoscopic tumour resection	~0.02mm (Positioning accuracy)	serial
NEUROBOT	Nanyang Technological Univ.	Supervisory Control	Skull base surgery	~0.01mm (Positioning accuracy)	parallel
Minerva (discontd)	Univ. of Lausanne	Supervisory control	Biopsies	Data not available	serial

8) NeuroBot- It is a neurosurgery robotic system developed in Nanyang Technological University for skull base surgeries [69]. It mainly consists of three parts- image guided motion planner and controller, parallel robot and an optical position tracking system. It assists the surgeon in the skull flap removal procedure. Generally the procedure takes about eight hours but, with the help of NeuroBot, it is reduced to two hours.

9) BrainLab Vector Vision Neuronavigation system- This is neuronavigation system developed by BrainLab which links a free hand probe with a computer image space on the pre-operative images of a patient with the help of a passive marker sensor system [70]. Intra-operative visualisation of the probe is possible with the aid of two cameras which emit infrared flashes which in turn are reflected by the passive markers both on the surgical tool and the Mayfield headrest. This system greatly enhances the efficiency of planning and performing of surgery of brain lesions.

2.8 Control Applications in Medical Robots

Control system is considered the brain of a robotic system. It ensures that a robot performance its tasks accurately and in a time bound manner. The performance requirement of a medical robot is much more stringent than its industrial counterpart as in the case of a medical robot, the safety of the patient and its operator is at stake. Hence, the design of control system is of prime importance in the development process of medical robot. Various control strategies have been implemented in medical robotic systems. In this section some of strategies which play an active role in accurate targeting of the target organ abnormality are discussed.

Lung tumour tracking: Adaptive tumour tracking system (ATTS) developed at the University of Wurzburg [71] tracks the lung movement in real time and gives input to the robot so as to compensate for the lung movement due to respiration. The tumour position input is given to a six DOF hexapod which moves the patient couch in such a way that a fixed spatial relationship is maintained for the tumour. A prediction model for the lung combined live tracking of lung was used to obtain tumour position. Three controllers were tested for the control of the Hexapod: naive feedforward control, PID and Model Predictive Controller (MPC). The simple naive feedforward control was able to reduce the tracking error by only 33%. MPC and PID controller

were able to reduce the error amplitude by 50% compared to the naive control. MPC was found to be more robust and accurate even when the breathing frequency and amplitude of the patient varied. PID controller performed well in case where the breathing pattern remained constant at the time of controller gain tuning. However, its performance deteriorated sharply when breathing variations were introduced in the tests.

HIFU-based breast surgery robot, FUSBOT-BS: A hybrid supervisory control was used in FUSBOT-BS, a HIFU-based surgical robot to ablate breast tumours, developed by the Biomechatronics group, NTU [60, 72, 73]. PID and robust controller are combined along with an estimator-based supervisor to form the hybrid supervisory controller. The model based robust control complements the PID controller especially in situations where the latter does not provide the desired accuracy. FUSBOT-BS has a four-DOF manipulator- Vertical axis (VA), Rotational axis (RA), Horizontal axis (HA) and the Orientation axis (OA). The experimental tests show a positioning error of less than 0.5mm [60, 72] where the supervisor in the developed hybrid controller successfully switches between the PID controller and Robust controller depending on the performance estimated for the current state of the system. The supervisor used in this work is an estimation based supervisor. In breast tumour ablation, the intra-operative tissue deformation is not major concern as much as in the case of neurosurgery and hence in a dynamic trajectory control was not required.

Compensation of physiological motion in robot-assisted surgery: Cortesao et al [74] proposed a control architecture in order to actively compensate for physiological motions during surgery. Motions such as heart beat motion make it extremely difficult for the surgeon to perform surgery on an organ. The control strategy uses two separate active observers (AOBs) for force control as well as physiological motion compensation. Direct model reference adaptive controller, along with the first AOB ensure the required closed loop dynamics for force control. The simulation results presented in the work shows that this control strategy was able to eliminate the effect of the introduced (both sinusoidal (2Hz frequency, 3N amplitude) and non-sinusoidal noise) by providing movement compensation of the surgical tool.

Ultrasound image-based visual servoing: Sauvee et al [75] proposed and tested an ultrasound image-based visual servoing method for achieving hand-eye synchronization for the surgeon while performing non-invasive surgery for heart valve replacement. They use a non-linear model predictive controller (NMPC) in order to control the movement of the surgical instrument. NMPC is an extension of Model Predictive Controller (MPC) by considering a non-linear systems and constraints. The proposed controller is tested by servoing a long thin instrument with two jaws attached to a 6-DOF robot based on ultrasound images. The controller successfully constraints the surgical tool within the ultrasound imaging probe field of view even in the presence of noise and modelling errors.

2.9 Image-guided Neurosurgery

Identifying and localizing accurately the desired abnormality or tissue inside the brain is one of the most challenging tasks of a neurosurgeon as the brain has a very complex structure and some parts may be indistinguishable visually. Technology has advanced in the field of imaging and robotics that reliable navigation and localization of surgical targets have become possible.

As described earlier, there are basically two approaches for stereotactic procedures: frame-based and frameless stereotaxy. Though frame-based procedures are considered the gold standard in localization technique, researches are carried out to replace this with the frameless procedure as it does not require head frames which are fixed invasively. In the case of frameless surgery, the target is localized with the help of pre-operative 3-D images and the intra-operative image of the patient. The aim of Image Guided Surgery (IGS) is to align/register the two set of images and present the accurately aligned image data to the surgeon or feed the information to the robotic system in a way that it aids navigation. Establishing correspondence between the pre-operative and the intra-operative images is done by image processing techniques like image registration, which is discussed in Section 2.9.

For brain tumour treatment with radiosurgery or other modalities like HIFU, the dexterity of a surgeon's hand is not required. In these cases, the accuracy for targeting the desired location is the criterion. Hence, use of a robotic system would be ideal for radiosurgery. It has better accuracy, repeatability and does not experience fatigue when compared to a human. The exact

location of the tumour is obtained through the image registration of the pre-operative and intra-operative images. This information is given to the robotic arm, which holds the radiation/HIFU modality, then accurately shifts the focus to the targeted area and shoots the beam. Prior to the surgery, the surgeon plans the entire treatment based on the pre-surgical images. An example of such system is the Cyberknife [11, 38, 55].

The Cyberknife system, shown in Figure 2.9, consists of a compact 130kg, 6 MV X-ray Linear Accelerator (LINAC), which is accurately positioned by a robotic arm that can position the LINAC with six degrees of freedom [30]. Two X-ray imaging devices (amorphous silicon detectors) are placed on either side of the patient's anatomy and these acquire images of the patient's skull intermittently during the treatment. These images are registered with digitally reconstructed radiograph derived from the pre-operative CT scan, which translates the position of the skull (the treatment site) to the LINAC coordinate frame. A control loop between the imaging devices and the robotic arm helps in adjusting the robotic arm so as to position the beam from the LINAC on to the desired target. The system presumes a fixed relationship between the skull and the tumour site.

Figure 2.9 (a) Schematic representation of the Cyberknife system [4], (b) X-ray imaging devices [76]

The workspace of the robotic arm is defined by a 3-D computer model which consists of all the objects within the reach of the arm. The robotic arm continually checks its position with the computer model to avoid collision. The workspace of the Cyberknife, for cranial radiosurgery, is a hemispherical volume centred on the coronal plane through the patient's head [30].

The Cyberknife dose distribution showed in a series of trial on a dosimetric phantom, an observed root mean square radial error of 1.8mm, which is the same accuracy as a typical stereotactic frame-based radiosurgical system [30].

2.10 Brain Shift

Currently available neurosurgical robotic systems [11] depend on the pre-operative images and external markers placed on the patient's head for the navigation of the surgical tool and subsequent targeting of abnormalities inside the brain. They assume that the spatial relationship between the brain abnormality (such as brain tumours) and the skull is fixed. But this is not the case in reality. Many studies have shown that the brain experiences a phenomenon called brain shift [8, 10, 77], whereby the brain tissues deform non-rigidly during a surgical procedure. The shift is caused due to several factors, such as leakage of cerebrospinal fluid (CSF), use of diuretics and anaesthetics, positioning of the patient's head, surgical manipulations (even when mechanical waves such as HIFU are used) and many other factors known and unknown[8, 10]. Therefore, as the surgery progresses, the information from the pre-operative images would become outdated and relying solely on pre-operative planning would lead to gross inaccuracies. Also, during the tumour resection or ablation, there is a possibility that the surrounding tissues will collapse into the space of the resected tumour. It has been shown that during neurosurgical procedures, there is deformation in brain tissues generally in the direction of gravity [77].

Brain shift happens continuously and dynamically and it happens differently in different parts of the brain. The maximum brain surface shift during tumour resection, through craniotomy (including the dura mater), can be as high as 50mm for large tumours [10]. For a minimally invasive neurosurgery, during craniotomy only a small region of the skull is removed and the dura mater is kept intact. So there is little or no loss of Cerebrospinal Fluid (CSF) and as a result the loss of cranial pressure will be very less. Hence, the displacement or deformation of the brain tumour/tissues in this case will be less compared to the case where the dura mater is removed but still significant.

In the intra-operative imaging studies conducted by Navabi et al (2001) [10] using MR imaging, brain shift in 25 patients during surgery were estimated. In 20 out of 25 cases, after craniotomy but before tumour resection, constant surface sinking in the direction of gravity was observed and also in almost all cases subsurface deformation were observed. The images were taken at four time points during the surgery- after positioning (as a baseline), after dural opening and CSF drainage, after tumour resection and after dural closure. Navabi et al reports that the maximum shift ranged from 0 (for small lesions) upto 50mm (for large lesions). They also observed that in all cases, the amount of shift decreased and also a brain volume increase towards the end of the surgery i.e., for the 3rd and 4th imaging. In the case of very large tumours, slight bulging was observed after craniotomy. Table 2.3 shows the deformation in brain at three stages of the surgery.

Table 2.3 Maximum brain shift and brain volume change at 3 surgical stages (baseline, after dural opening, after resection, dural closure) [7]

Surgical stages	Maximum brain shift (mm)				Brain Volume change (%)			
	Baseline	1 st	2 nd	3 rd	Baseline	1 st	2 nd	3 rd
Small lesions (<15ml)	0	12.7±3	21.1±12	11.6±4	100	96.2±3	88.5±6	91.5±7
Intermediate (15-40ml)	0	15.8±7	23.8±12	12.7±8	100	96.4±2	90.4±10	92.3±7
Large (>40ml)	0	19±7	37.6±14	11.8±3	100	97.3±4	81.8±4	85.9±8

In Letteboer et al (2005) [8], the rigid component of brain shift prior and after the dural opening is estimated by comparing intra-operative ultrasound images to the pre-operative MRI for 12 patients. The authors observed the brain shift in the direction parallel and perpendicular to gravity and also the angle of the main direction of the shift w.r.t. the direction of gravity. The average brain shift measured prior to the dural opening was 3mm parallel (maximum of 7.5mm) and 3.9mm perpendicular to the direction of gravity (maximum of 8.2mm). After the opening of dura mater, the average shift was 3.2mm parallel to the direction of gravity and

5.3mm perpendicular to it. Figure 2.10 shows the total brain shift before and after the dural opening and its direction with respect to gravity for the 12 patients.

Figure 2.10 Total brain shift and its direction w.r.t to direction of gravity in the case of the 12 patients [8]

2.10.1 Methods to Estimate Brain shift

There have been several studies to estimate brain shift so as to enable the surgeon to accurately target the brain abnormality during surgery. Mainly two methods have been studied- 1) intra-operative imaging, 2) biomechanical modelling the brain deformation[8]. It has been showed in many studies that the brain deformation is dynamic and unpredictable as there are number of factors such as positioning of the patient, surgical manipulation, leakage of cerebrospinal fluid and so on that influence this deformation [10, 16].

Some of the models that have been developed for this purpose are discussed below:

1. Damped spring mass model: This model was proposed by Skrinjar et al 2001[16]. The model was designed for fast computation, at least at the speed of the actual brain deformation. The assumption of the model was that brain deformation is relatively small compared to the brain size and a slow process. The model consists of a set of interconnected discrete nodes and the Kelvin solid model is used to model each connection. Each node represents a tiny part of the brain and its mass depends on the size of the volume and local tissue density. A linear stress-strain relation is used in the model as it gives a good approximation for small deformations. Here the parameters considered were stiffness coefficient and damping coefficient.

The problem with this model is that parameter identification is extremely difficult as the parameter values vary for different tissues in the brain and estimating the parameters locally is very difficult. Hence in this work, the brain is considered homogenous. The parameters are estimated offline and by estimating for a large number of patients and then taking the average, the values can be used for brain shift estimation in future patients. But this too is difficult, as the model parameters are mesh dependent. The model is updated during the surgery based on the intermittent intra-operative surface data of the deformation. However the problem was that the updating of the model was completely ad hoc i.e., it is not known what is the best way to modify the spring-mass model based on the surface data.

Due to these two problems, a model based on continuum mechanics was proposed by the same group. The damped spring mass model was tested on one patient and an improvement was observed compared to the case where there is no brain shift compensation. Also, it was possible to estimate the deformation in real-time i.e., as fast as the actual deformation.

2. Continuum mechanics based brain model: This model solves the two problems in the damped spring-mass model- parameters are not dependent on the model mesh and it updates the model in a correct way based on the intra-operative data mathematically and also deform the pre-operative model according to the current state. The proposed model is a relatively simple one. Only the elasticity and incompressibility of the tissues are taken into account. Since brain deformation is very slow, the dynamic component of the deformation was neglected. The brain tissues are assumed to be isotropic materials. This model is computationally expensive compared to the spring mass model. However, this model can model sinking as well as bulging cases in brain deformation [16].
3. Miga et al 1999 [9, 14] modelled the brain using the consolidation theory where the tissues are represented as a solid matrix saturated by a interstitial fluid. The approach is based on the finite element rendering of consolidation theory where the continuum mechanics is characterized by an instantaneous deformation followed by an additional

displacement over time due to the draining of the interstitial fluid when subjected to load. The effect of gravitational force was added to it. The model was used in four clinical cases and a registration error (due to brain shift) of the order 6mm was estimated with an error of 1.2mm [14] thereby recapturing the 79% of the deformation. The biggest drawbacks of this technique are the heavy computation involved in the finite element computation at each update and the determination of tissue properties of the brain in vivo.

4. A simple linear hyper-viscoelastic constitutive model for tissue deformation was proposed in Miller 1999 [15].

It is also important to note that deformation models have lower precision and also very low reliability [14, 16] because it is almost impossible to accurately model a highly dynamic and unpredictable process such as brain deformation. Also the computational cost for solving complex models is very high. One of the plus points of using deformable models for intra-operative guidance is its cost effectiveness compared to imaging modalities such as MRI and CT.

The alternative to developing a deformation model for the brain for real-time tissue deformation estimation is intra-operative imaging and image processing techniques. This would give the surgeon the actual state of the tissue at the time of imaging. MRI and CT imaging are the most commonly imaging modalities used for diagnosis of brain tumours and also as an aid in neurosurgeries. It has been shown that to track and compensate for brain shift, one needs to monitor/image the brain as frequently as possible [10]. Though the above mentioned modalities give high quality images, they are not suitable for continuous intra-operative monitoring as they require the surgery to be stopped intermittently so as to take the images. They are expensive and the material of the surgical equipments needs to be CT/MRI compatible. Also, it is practically impossible to take real-time and/or frequent images during the course of surgery since the image acquisition procedures takes a lot of time (approx. 60minutes) [22]. Some non-invasive neurosurgical robotic systems such as Cyberknife© [11], use X-ray imaging for monitoring and updating during the surgery. The disadvantage of using X-ray is the radiation exposure of the patient as images need to be taken several times during the

course of the surgery. This is harmful especially to old people and infants which are the fastest growing demographics in the brain tumour patient population [32].

In recent years, there has been an increased focus on the use of ultrasound (US) imaging for real-time, intra-operative imaging as it is cheaper, easier to integrate with the robotic system and has no adverse effect on healthy tissues. For ablative procedures where temperature is an essential feedback parameter, it is also possible to do real-time temperature monitoring using US imaging [47]. It is possible to take images several times per second which is desirable for accurate and real-time tracking of the deformation [22]. The most serious concern with ultrasound imaging, however, is its poor resolution and variability of image quality for different users. In neurosurgery, this problem is even more accentuated due to presence of bone structure (skull) in the vicinity of the target. Though there has been some improvement in the ultrasound image quality, the specificity in detecting remaining parts of the tumour at the end of the surgery continues to be unsolved [78].

2.11 Image Registration

Image registration is the process of aligning corresponding features of images from the same modality or from different modalities [25, 79, 80]. For the past 25 years, a huge amount of money and resources have been invested in the development and advancement of newer and better image technologies. Each generation of imaging modalities, such as X-ray, MRI, CT, ultrasound, have been faster and of higher resolution and quality. Medical imaging is about establishing shape, structure, size, and spatial relationships of anatomical structures or any pathology or abnormality within the patient. Medical Imaging can also help in obtaining functional information which reveals physiological activities of the required tissues within the patient[25]. Establishing correspondence between medical images and the equivalent structure in the body is very important in the analysis and interpretation of medical images. Before, aligning and finding correspondence between images used to be done by mental visualisation. This is a very challenging task especially when the structure is very complex and also this is more prone to error. However, images alignment and correspondence can be done with the

help of image registration and fully automated algorithms are available for a number of application.

Medical image registration has a wide range of possible applications [25] like

- 1) Combining information from images of different modalities.
- 2) Monitoring changes in the size, shape or image intensities over a time interval ranging from few seconds to even several years.
- 3) Relating pre-operative images or pre-surgical plans to the intra-operative images of the patient in the operating room during an image-guided surgery or in the treatment suite during radiation therapy.
- 4) Matching of individual anatomy to standardized atlases.

The number of parameters needed to describe a registration transformation is referred to as the degrees of freedom. This depends on the dimensions of the images and also their constraints of the structure which was imaged.

Figure 2.11 Rotation of coordinate frame of image XYZ to X'Y'Z'; α , β , γ are the rotations about the x, y, z axes respectively

For a rigid body transformation, the transformation can be described with just translation and rotation. In the case of 2D-to-2D image registration, the DOF will be three i.e., two translations and one rotation and for 3D-to-3D registration, the DOF is six i.e., three translations and three rotations.

$$T_{rigid}(x) = R x + t, R\text{-rotation matrix, } t = \{t_x, t_y, t_z\}^T, x = \{x, y, z\}^T \quad (2.1)$$

$$R = \begin{bmatrix} \cos\beta\cos\gamma & \cos\alpha\sin\gamma + \sin\alpha\sin\beta\cos\gamma & \sin\alpha\sin\gamma - \cos\alpha\sin\beta\cos\gamma \\ -\cos\beta\sin\gamma & \cos\alpha\cos\gamma - \sin\alpha\sin\beta\sin\gamma & \sin\alpha\cos\gamma + \cos\alpha\sin\beta\sin\gamma \\ \sin\beta & -\sin\alpha\cos\beta & \cos\alpha\cos\beta \end{bmatrix} \quad (2.2)$$

where, α , β , γ are the rotations about the x , y , z axes respectively and $\mathbf{t}$ represents the translation along the three axes.

Affine transformation has 12 degrees of freedom. It allows a combination of rigid body motion, scaling and skewing about any of the three axes. In this transformation, any straight line in the image is transformed into a straight line in the other and parallel lines are preserved. This is useful in compensating for scanner errors and aligning images from different subjects.

Figure 2.12 Ultrasound and MRI image after the dural opening is shown in the top row; the bottom row shows the tumour contours in both images; we can clearly see in the fourth image that there is a mismatch between the tumour contours in the US image and MRI

In non-rigid registration, many more degrees of freedom are required. Two general categories of non-rigid registration occur: registration of images to an atlas or images from another individual or registration of tissue that deforms over time [25]. Generally, to make the

registration computationally tractable and physically plausible, constraints on the allowed deformation are applied. These constraints depend on the application for which it is used.

Figure 2.13 The US image and MRI shown in Figure 2.12 are registered using a mutual information based rigid registration algorithm

Non-rigid problems can be broadly classified [81] into 1) Intra-modality intra-subject registration: The images to be registered are acquired from the same person and by the same scanner. A series of MR images are taken over time to assess the response of tumour to radiation and if this involves non-rigid tissues or organs then non-rigid registration are performed; 2) Intra-modality inter-subject registration: Here the images are taken by the same scanner but from different subjects. These are generally used for atlas based segmentation or statistical atlas creation; 3) Inter-modality intra-subject registration: Images to be registered are acquired from one subject but using various devices. This involves integrating and fusing images from different modalities like MR, CT, US or other imaging modalities; 4) Inter-modality inter-subject registration: Images from different modalities and from different subjects are to be registered in this case.

2.12 Various Registration Algorithms

Point-based Registration

Point-based registration involves identifying corresponding 3D points in the images (fiducial markers or fiducial points) to be aligned, registering the points, and inferring the image transformation from the transformation determined from the points. The fiducial points can consist of anatomical landmarks, akin-applied markers or bone-implanted markers. Here the objective is to find corresponding sets of points $\{x_a\}$ in the image A and set of points $\{x_b\}$ in the

image B and then inferring the transformation based on these two set of points. The most common approach is the orthogonal procrustes problem.

The orthogonal procrustes problem is an optimization problem of the least square type. Given two configurations of N points of D dimensions: $P = \{p_i\}$, $Q = \{q_i\}$, we try to find the transformation T such that it minimized $G = |T(P) - Q|^2$ [25].

Figure 2.14 Schematic representation of patient-to-image registration using point-pair matching [3]

Errors in rigid body point registration

There are three error metrics for point based registration [25, 82]: 1) Fiducial Localization Error (FLE) is a measure of the accuracy with which one can locate a given fiducial. This depends on the accuracy with which the user can locate the fiducial on the images and on the patient and also on the intrinsic accuracy of the localization device. 2) Fiducial Registration Error (FRE) is the root mean square residual error on the fiducial after transformation. FRE alone is not a good measure for registration accuracy [82, 83]. This is because, in cases where FRE is the sole measure of accuracy, there is a tendency to ignore fiducials with high FRE until the mean FRE falls below a certain value. This can lead to poor registration of the target especially if it lies at a distance from the low FRE fiducials. 3) Target Registration Error (TRE) is the most clinically relevant metric. It is the measure of the accuracy by which a point other than the fiducial can be located.

Fitzpatrick et al. in 'Predicting error in rigid body point-based registration' has given a formula relating FLE and TRE and the configuration of the landmarks [82]

$$\langle TRE^2(r) \rangle = \frac{\langle FLE^2 \rangle}{N} 1 + \left(\frac{1}{3} \sum_{k=1}^3 \frac{d_k^2}{f_k^2} \right) \quad (2.3)$$

where N is the number of fiducial points, f_k is the rms distance of the fiducials to the principal axis, k , of the point distribution, d_k is the distance from this same axis to the target point, r and $\langle . \rangle$ stands for expected value.

Surface Matching

A major problem of the point-based registration is that the fiducials are likely to shift positions especially the skin markers. To place fiducials on the bone, it would require an invasive procedure. Also the markers have to be placed on the patient before the image data acquisition and often the patient would have already undergone diagnostic imaging which results in high cost and additional exposure to radiation in the case of CT [84]. A schematic representation of surface matching is presented in Figure 2.15.

Figure 2.15 Schematic representation of patient-to-image registration using surface matching [36]

Iterative Closest Point Algorithm (ICP) is a widely used surface based registration algorithm in medical imaging application. The two sets of data to be registered are delineated from the radiological images or the model derived from these images and the data obtained from the stereo video taken during the operation. It is designed to work with different representations of surface data like point sets, line segment sets (polylines), implicit surface, parametric curves, triangle sets, implicit surfaces, and parametric surfaces [25]. A picture from ICP experimental tests is shown in Figure 2.16.

Figure 2.16 The markers on ultrasound (US) image (top left) and Charged Coupled Device (CCD) image (top right) are segmented; in ICP, the selected point set on US image (data surface p) is then identified on the CCD image (model surface X); the data shape is registered to the model shape by iteratively finding the model points closest to the data points

As the name suggests, this is an iterative algorithm and has two stages. During the first stage, it tries to identify the closest model point for each data point and, in the second stage, it involves computing the least square rigid body transformation relating these two point sets [25]. The algorithm then re-determines the closest point set and repeats the steps until it finds local minimum match between the two surfaces.

One data surface p , is first converted to a set of points [85] and the model data surface is retained as its original representation. The first stage involves identifying for each point on the data surface p , a point on the model surface X . This is the point x for which the distance d between p_i and x is minimum[25],

$$d(\mathbf{p}_i, \mathbf{X}) = \min_{\mathbf{x} \in \mathbf{X}} \|\mathbf{x} - \mathbf{p}\| \quad (2.4)$$

Iterative Closest Point algorithm gives good performance for rigid registration problems. However, in order to ensure reliable registration, the two point sets should be 'close' to each other. For this reason, ICP fails to give reliable performance in non-rigid registration where it cannot be assumed that the point sets will be close [25, 86].

Voxel Similarity Measure

Registration using voxel similarity measure involves calculating the registration transformation T by optimizing some measure calculated directly from the voxel values in the images rather than from geometrical structures such as points or surfaces derived from the images. This is being used in mono-modality as well as multimodality and rigid as well as in non-rigid registration. Their basic principle is to maximize a criterion by comparing the intensity value at corresponding voxels [87]. For registration using voxel similarity measures, whether the registration is intra-modality or inter-modality is very important, unlike in the case of point-based and surface based matching. This is because in the case of multi-modal image registration, the intensities in the image have no simple relationship as they are from different devices. Also, intensity based method may give good performance even in case of intra-modality registration for imaging modalities such as ultrasound imaging where there can be drastic changes in the intensity due to shadowing and reflections of the ultrasound signals. Some of the most widely used voxel similarity measures are [25]:

1) Minimizing Intensity Differences – In this, the sum of the square of the intensity differences between images are minimized during registration. It is given by [25]

$$SSD = \frac{1}{N} \sum_{\mathbf{x}_A \in \Omega_{A,B}^T} |A(\mathbf{x}_A) - B^T(\mathbf{x}_A)|^2 \quad (2.5)$$

where $\mathbf{x}_A$ are the voxel locations in the image A, $\Omega_{A,B}^T$ is the overlap domain between image A and image B and N is the number of voxel in that domain. It is divided by N to normalize the measure so as to make it invariant with the number of voxels. This is the optimum measure only when the images differ by Gaussian noise and hence this measure cannot be used for

multimodal registration [25]. This criterion is rarely correct in the case of intra-modality registration too as there are chances of noise from other sources during imaging and also the object can change between acquisitions.

2) Correlation Technique: In this measure, the assumption is that there is a linear relationship between the intensity values in the images. The optimum similarity measure is the correlation coefficient CC which is given by [25]

$$CC = \frac{\sum_{x_A \in \Omega_{A,B}^T} (A(x_A) - \bar{A}) \cdot (B^T(x_A) - \bar{B})}{\left\{ \sum_{x_A \in \Omega_{A,B}^T} (A(x_A) - \bar{A})^2 \cdot \sum_{x_A \in \Omega_{A,B}^T} (B^T(x_A) - \bar{B})^2 \right\}^{\frac{1}{2}}} \quad (2.6)$$

where $\bar{A}$ and $\bar{B}$ are the mean of the voxel value in image A and B respectively within the overlap domain $\Omega_{A,B}^T$.

Information Theoretic Techniques

Image registration can be described as maximizing the amount of shared information in the two images. Here the registration metric is the amount of information.

Mutual Information (MI) based registration is an example of registration based on information theory. The algorithm assumes the existence of two data volumes in which one is stationary (primary) and the other (secondary) is altered iteratively until the optimal alignment is achieved, which corresponds to the maximum of the mutual information function. The MI function is given by [88]:

$$I(A, B) = \sum_a \sum_b p(a, b) \log \left(\frac{p(a, b)}{p(a)p(b)} \right) \quad (2.7)$$

where $p(a)$, $p(b)$ are the probability density functions of the data volumes A and B respectively, $p(a, b)$ is the joint probability density function of the voxel intensities in the overlapping domain. One of the disadvantages of using mutual information algorithm is that MI is calculated on a pixel basis i.e., it calculated MI between two corresponding pixels without considering the

pixels in the neighbourhood. Hence, most of the spatial information of the feature is lost in the process [89].

Probability Estimation based techniques

One of the most popular probability density estimation based algorithms is the Coherent Point Drift (CPD) algorithm [85]. CPD is a point-based rigid/non-rigid registration framework. In this method, a Gaussian Mixture Model is fitted to one of the point sets to be registered and the other point set is taken as the initial position of the GMM centroids. The movement of the GMM centroids from its initial position to the final position is considered a temporal motion process. In CPD, no assumption is made about the underlying transformation. The movement of the GMM centroid is carried out by applying a motion coherence constraint. Motion coherence theory states that points close to each other tend to move coherently. This regularisation is achieved by penalizing all the orders of underlying velocity field of the motion. The convergence of the two point set is achieved using an Expectation Maximisation method [85, 90]. This framework has been found to be robust in the presences of outliers and noise and also computationally fast compared to other similar algorithms like Thin Plate Spline-Robust Point Matching algorithm [91, 92].

2.13 Summary

The anatomy of the brain was studied in the chapter as it is extremely important understand it in order to devise a control strategy for neurosurgery. Similarly, the most commonly occurring types of brain tumour and their region of occurrence were understood. From this study, it was clear that about 60% of the brain tumours were superficial tumours i.e., they occurred close to the surface of the brain. Currently available treatment options were explored- invasive, minimally invasive and non-invasive methods. Stereotactic Radiosurgery treatment was studied in more details so as to gain an understanding of the principles of both frame-based and frameless surgery. Similarly, a non-invasive modality High Intensity Focused Ultrasound, which has shown encouraging results in recent years, was also investigated.

The role of robotics in medicine was studied as to understand the range of tasks that robots are capable of performing in the surgical environment. Since this work is focused on neurosurgery, it is important to have knowledge of neurosurgical robots that are currently available in the market as well as being developed in labs.

The phenomenon of intra-operative brain deformation, called brain shift, was investigated. The nature and extent of the deformation was understood. It was found that the maximum deformation observed is in the direction of gravity and the maximum deformation observed is 50mm in case of large tumours. Two methods for the estimation of brain deformation were studied- Brain modelling and Intra-operative imaging. Due to the large number of factors which influence brain deformation and also due to the computational requirement needed to implement a real-time estimation, brain modelling was found to be not suitable for the problem targeted in this work. With the help of real-time intra-operative imaging using modalities like ultrasound imaging, it is possible to compensate for the deformation in real-time. Various image registration algorithms were explored and understood as it plays a major part in the development of control for an image-guided neurosurgical robot.

CHAPTER 3. DYNAMIC IMAGE REGISTRATION FOR INTRA-OPERATIVE BRAIN SHIFT ESTIMATION- METHODOLOGY

In minimally or non-invasive neurosurgery, the most critical aspect in ensuring accurate treatment delivery is tracking the deformation of the brain during the course of the surgery. The deformation of the brain, called brain shift, is highly unpredictable and dynamic in nature. The amount of shift and its nature varies from the patient to patient and or from one region of the brain to the other. The factors that influence this deformation are many, ranging from gravity to surgical manipulation, variation in intra-cranial pressure to loss of cerebro-spinal fluid and many reasons yet to be discovered. Due to the nature of brain shift, it is necessary that the estimation of this deformation be performed in real-time. Hence the two most important criteria for the selection of method for brain shift estimation are the computation and image acquisition time and accuracy.

Biomechanical modelling of the brain, real-time intra-operative imaging and also a combination of both has been proposed as a solution to the real-time estimation of brain shift. However, due to the complexity of accurately modelling the brain and its deformation and also due to the fact that computation of just a model would be computationally expensive and unreliable, in this work the author proposes to employ the method of real-time intra-operative imaging for the tracking of deformation.

Various imaging modalities were explored in the previous chapter for this purpose. Ultrasound imaging was found to be the most suitable due to its compactness, compatibility, cost and also its fast image acquisition time compared to MRI, CT and X-ray imaging. The major drawback in using ultrasound imaging is the poor resolution and noisy nature of ultrasound images. This drawback can be alleviated to a great extent with the use of suitable noise filters.

The focus of this chapter is on the 'Image Processing' unit in the general neurosurgery robotic system depicted in Figure 1.1. This chapter discusses and formulates the various image processing techniques used to estimate the dislocation and the deformation of the brain during the surgery. A tracking algorithm is also explained for the continuous tracking and updating of

the treatment plan in order to provide the neurosurgical robot with current position of the target. In the proposed dynamic deformation tracker, for the dislocation estimation, a computationally light template matching algorithm is employed and for the estimation of the non-rigid deformation, a point-based Coherent Point Drift (CPD) algorithm is used.

3.1 Estimation of Dislocation and Deformation of the Brain Tissue

In Section 2.10, the author discusses the nature of brain shift, the different methods used to estimate brain shift. In this research the author employs intra-operative imaging method for the real-time brain shift estimation and target tracking. Taking into account the importance for fast and real-time estimation, the author found ultrasound imaging as most suitable for the task.

From the literature study, the author observes the following points regarding brain deformation tracking, 1) brain shift has both a rigid as well as non-rigid component to it. In order to accurately target an abnormality in the brain, one has to estimate the dislocation as well as the deformation that is happening in the brain intra-operatively, 2) since intra-operative imaging will be performed frequently and in real-time, the deformation between successive images will be small. However, the tracking algorithm should allow for estimation of large deformation as well because deformations can be large in the region where there is surgical manipulation, 3) algorithm with less computation time should be employed if there are multiple algorithms which can give the required accuracy and 4) the tracking algorithm must be able to handle noise in the images as ultrasound images have poor signal to noise ratio.

The schematic representation of the strategy for the dynamic deformation tracker is shown in Figure 3.1. For the dynamic tracking of the tumour position, a two-stage approach is proposed in this work. The task of deformation estimation is broken down into two stages so as to reduce the complexity and computation time. In the first stage, the dislocation of the target is estimated. This stage provides the gross position information of the target and also reduces the image search space for the second stage. In the second stage, a non-rigid image registration is performed on the segmented feature which provides the deformation estimation of the desired feature. The input to the dynamic deformation tracker are the intra-operative ultrasound

images captured at different points of time- one captured at the time of previous estimation and the other is the current image. For the estimation of the deformation, we could register the first US image captured just before the surgery and the current (latest) image captured. However, this would lead to large deformation/dislocation between images as the surgery progresses. Hence, by making use of the temporal continuity of deformation of the brain, we register the image captured before previous estimation and the current image so as to restrict the amount of deformation between images.

Figure 3.1 Schematic representation of dynamic deformation tracker

The dislocation and deformation estimation is then used to update the position of the treatment points specified during the treatment planning stage which in turn is used to give input to the neurosurgical robot about the next target point. For the first stage, a computationally light and fast template matching algorithm was used to estimate the dislocation of the target. The second stage, which estimates the non-rigid deformation, uses a point-based non-rigid coherent point drift (CPD) image registration.

3.1.1 Estimation of Tumour dislocation

Studies have shown that the major component of the brain shift is the sinking of the brain tissues in the direction of the gravity (i.e., almost linear) [10, 77]. Maximum dislocation of 50mm have been reported in surgeries where large tumours have been removed [10]. The pace at which the deformation happens is also seen to be very slow. A neurosurgery for tumour

resection procedure typically takes 6-7 hours for its completion, which means the deformation happens at an average speed of only 0.002mm per second in the worst case scenario (maximum dislocation of 50mm). The effect of brain shift can be minimized to a great extent if the treatment time can be reduced drastically. Hence, the computation time of the dynamic tracking algorithm is a very important factor in the accuracy of the overall robotic neurosurgery system.

Figure 3.2 Block diagram of the template matching algorithm

The template matching algorithm [93] was used for the estimation of dislocation of the target (tumour) as it is computationally fast and simple to implement. In this algorithm, the grayscale value of a template image is scanned throughout the Region of Interest (ROI) and the area with the maximum correlation is segmented. The dislocation is calculation based on the distance in pixel co-ordinates of the segmented feature and the pixel size of the US images. Figure 3.2 shows the block diagram of the template matching algorithm.

$$Correlation = \frac{\sum_{i=0}^{N-1} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=0}^{N-1} (x_i - \bar{x})^2 \cdot \sum_{i=0}^{N-1} (y_i - \bar{y})^2}} \quad (3.1)$$

where x is the template image, $\bar{x}$ is the average gray level in the template image, y is the current section of the reference image, $\bar{y}$ is the average gray level in current section of the reference image and N is the number of pixels in the template image.

Using a computationally light algorithm provides gross position information about the tumour quickly, thereby enabling real time estimation, which can be fed to the surgeon or the robot controller for tool positioning.

Figure 3.3 Tracking target in intra-operative images taken at $t=0$ and $t=1$ in template matching stage

Two ultrasound images from the real-time intra-operative imaging system acquired at two different times are compared to obtain the dislocation information. A template image of the target from the first ultrasound image taken at time $t=0$ is used to estimate its dislocation at $t=1$ from the intra-operative image taken at $t=1$. The dislocation information is acquired based on the previous updated location of the target. Figure 3.3 shows a representation of images taken at two different instances ($t=0$ and $t=1$).

3.1.2 Estimation of Non-rigid deformation

For the estimation of the deformation of the brain, image registration techniques can be used. Registration can be rigid or non-rigid. However, the deformation of the brain tissue during neurosurgery has been observed to be non-rigid in nature [8, 10, 18, 77]. There are various non-rigid image registration algorithms such as Iterative Closest Point algorithm (ICP) [94] and Thin Plate Spline-Robust Point Matching algorithm (TPS-RPM) [91]. ICP is a widely used surface based registration algorithm in medical imaging application. In this, two point sets, delineated from the images, are registered. As the name suggests it is an iterative method. However, ICP has shown to poorly perform for non-rigid transformation [25, 86]. TPS-RPM is a point based non-rigid registration algorithm which uses thin plate spline to parameterize the non-rigid transform. TPS penalizes only the second order derivatives of the transformation and hence in three or higher dimension problems, the solution will not work [85, 90].

In this work, the author adopted a point-based non-rigid registration algorithm called the Coherent Point Drift (CPD). CPD is a point set registration algorithm which considers the registration of two point set as a problem of probability density estimation. In this algorithm, one point set is taken as the Gaussian Mixture Model (GMM) centroids and the other set as the data points. The fitting of the GMM to the data points is a maximum likelihood estimation problem. The basis of this alignment algorithm is the Motion Coherence Theory [95] i.e., points close to each other tend to move coherently. Motion coherence penalizes derivatives of all orders of the underlying velocity field and hence, the CPD algorithm forces the GMM centroids to move coherently in such way that it retains the point sets' topology [90]. This algorithm has been developed for both rigid and affine registrations as well as for non-rigid point set registration. Since the brain deformation has been clearly shown to be non-rigid, only the non-rigid registration part of the algorithm was implemented. For non-rigid registration, the motion coherence constraint is imposed on the points by regularization of the displacement field thereby imposing smoothness to the transformation. The algorithm [85, 90] is described in brief below.

Let,

$$\text{Template point set, } Y_{M \times D} = (y_1, y_2, \dots, y_M)^T \quad (3.2)$$

$$\text{Reference point set, } X_{N \times D} = (x_1, x_2, \dots, x_N)^T \quad (3.3)$$

where, D is the dimension, M and N are the number of points in point sets Y and X respectively. The template point set represents the point set extracted from the US image captured during the previous estimation and the reference point set represents the point set from the current US image. Y represents the GMM centroids and X represents the data points generated by the GMM.

The GMM probability density function with additional uniform distribution, $p\left(\frac{x}{M+1}\right) = 1/N$, in order to account for the noise and outliers is given by

$$p(x) = w \frac{1}{N} + (1 - w) \sum_{m=1}^M \frac{1}{M} p(x|m) \quad (3.4)$$

where, $w, 0 \leq w \leq 1$, denotes the weight of the uniform distribution. The expectation maximization algorithm [96] is used to align the point sets. For this, the distribution is re-parameterized using a set of parameters θ . The parameters are then estimated by maximizing the likelihood or by minimizing the negative log-likelihood function

$$E(\theta, \sigma^2) = -\sum_{n=1}^N \log \sum_{m=1}^{M+1} P(m)p(x|m) \quad (3.5)$$

The correspondence probability between the two point y_m and x_n is defined as the posterior probability of the GMM centroid which is given by $P(m|x_n) = P(m)p(x_n|m)/p(x_n)$. The parameters θ and σ^2 are calculated using the expectation maximisation (EM) algorithm. In EM algorithm, the old parameter values (starting values) are first guessed and then the Bayes' theorem is used to calculate the a posteriori probability distribution, $P^{old}(m|x_n)$, of the GMM components. This is the Expectation step (E-step) of the algorithm. By minimizing the expectation of the complete negative log likelihood function,

$$Q(\theta, \sigma^2) = \frac{1}{2\sigma^2} \sum_{n=1}^N \sum_{m=1}^M P^{old}(m|x_n) \|x^n - T(y_m, \theta)\|^2 + \frac{N_p D}{2} \log \sigma^2, \quad (3.6)$$

$$N_p = \sum_{n=1}^N \sum_{m=1}^M P^{old}(m|x_n) \leq N \quad (3.7)$$

$$P^{old}(m|x_n) = \frac{\exp \left\{ -\frac{1}{2} \left\| \frac{x_n - T(y_m, \theta^{old})}{\sigma^{old}} \right\|^2 \right\}}{\sum_{k=1}^M \exp \left\{ -\frac{1}{2} \left\| \frac{x_n - T(y_k, \theta^{old})}{\sigma^{old}} \right\|^2 \right\} + c},$$

$$c = (2\pi\sigma^2)^{D/2} \frac{w}{1-w} \frac{M}{N} \quad (3.8)$$

the new parameters are found. This is the Maximisation step (M-step) of the algorithm. By minimising Q , which represents the upper bound for the function E (equation 3.5), it minimises the function E . The algorithm is an iterative algorithm where it moves from the E-step to M-step and back till the point of convergence.

The non-rigid transformation is defined as $T(Y, \vartheta) = Y + \vartheta(Y)$, where Y is the initial position and ϑ is the displacement function. ϑ is regularized so as to impose smoothness on the transformation, as the underlying transformation of the CPD framework is based on Motion Coherence Theory (MCT). As mentioned before MCT states that points close to each other

moves coherent and hence the displacement function, ϑ , needs to be smooth. The negative log-likelihood function after the addition of the regularization term [90] is

$$f(\vartheta, \sigma^2) = E(\vartheta, \sigma^2) + \frac{\lambda}{2} \phi(\vartheta), \quad (3.9)$$

where ϕ is the regularization term, λ is a trade-off parameter and the E is the negative log likelihood function. The displacement function is estimated using variational calculus. The minimization of the regularized negative log-likelihood function is basically equivalent to the minimization of the objective function,

$$Q(\theta, \sigma^2) = \frac{1}{2\sigma^2} \sum_{n=1}^N \sum_{m=1}^M P^{old}(m|\mathbf{x}_n) \|\mathbf{x}^n - (\mathbf{y}_m + \vartheta(\mathbf{y}_m))\|^2 + \frac{N_{pD}}{2} \log \sigma^2 + \frac{\lambda}{2} \|\mathbf{P}\vartheta\|^2 \quad (3.10)$$

where $\phi(\vartheta)$ is defined in the Reproducing Kernel Hilbert Space (RKHS) as:

$$\phi(\vartheta) = \int_{RD} \frac{|\tilde{v}(s)|^2}{\tilde{G}(s)} ds, \quad (3.11)$$

where, G is a Gaussian. The functional form of ϑ is found [90] using calculus of variation,

$$\vartheta(\mathbf{z}) = \sum_{m=1}^M w_m G(\mathbf{z}, \mathbf{y}_m) + \phi(\mathbf{z}) \quad (3.12)$$

Equation (3.12) is solved at $\mathbf{y}_m$ to obtain the coefficients w_m

$$(\mathbf{G} + \lambda \sigma^2 d(\mathbf{P}\mathbf{1})^{-1})\mathbf{W} = d(\mathbf{P}\mathbf{1})^{-1}\mathbf{P}\mathbf{X} - \mathbf{Y} \quad (3.13)$$

where, $\mathbf{W}_{M \times D} = (w_1, w_2, \dots, w_M)^T$, $G_{M \times M}$ is a kernel matrix with elements $g_{ij} = G(\mathbf{y}_i, \mathbf{y}_j) = e^{-\frac{1}{2} \|\frac{\mathbf{y}_i - \mathbf{y}_j}{\beta}\|^2}$, $d^{-1}(\cdot)$ is the inverse diagonal matrix.

$$\sigma^2 \text{ is given by, } \sigma^2 = \frac{1}{N_{pD}} (tr(\mathbf{X}^T d(\mathbf{P}^T \mathbf{1})\mathbf{X}) - 2tr((\mathbf{P}\mathbf{X})^T \mathbf{T}) + tr(\mathbf{T}^T d(\mathbf{P}\mathbf{1})\mathbf{T})) \quad (3.14)$$

The transformed point set is given by:

$$\mathbf{T} = \mathbf{T}(\mathbf{Y}, \mathbf{W}) = \mathbf{Y} + \mathbf{G}\mathbf{W} \quad (3.15)$$

The algorithm is summarised in the flowchart shown in Figure 3.4.

Figure 3.4 Flowchart of CPD algorithm

3.2 From Estimation to Tracking algorithm

In the previous section, the method to estimate the dislocation and non-rigid deformation were explained. The dislocation of a feature between two images were estimated using template matching algorithm and the deformation was estimated by registering two images using the CPD algorithm. However, in order to update the treatment plan, we have to estimate from the first image (US_1) to current image (US_n) sequentially before targeting each treatment point specified in the treatment plan. One way to obtain the shift is to directly estimate the dislocation and deformation from the first image, which is taken just before the surgery, and the current image. However, the deformation between these two images could be large and hence computation time and accuracy could be affected.

In this work, we estimate the deformation by exploiting the temporal continuity of the brain deformation. Rather than using the first and current images, the author proposes to utilise the deformation information obtained up to US_{n-1} and compose it with the deformation between US_{n-1} and US_n . Hence the new deformation would be,

$$T_{US}(n) = dT_{US}(n) + T_{US}(n - 1) \quad (3.16)$$

This method is depicted in Figure 3.5. Using this method, the registration would much easier as the deformation between closely captured images would be small.

Figure 3.5 Tracking algorithm computing deformation using temporal continuity of brain deformation

This method helps in continuous and real-time estimation of the deformation (and in turn continuous and real-time tracking of the target) with the help of intra-operative ultrasound images captured before estimation of the deformation. By employing this tracking algorithm, the author proposes to provide the robot with updated position of the target points by compensating for the intra-operative brain shift in real-time so as to ensure accurate delivery of treatment.

3.3 Summary

In this work, intra-operative imaging and image processing techniques were used for the real-time estimation and tracking of brain shift. The author proposes a two-stage deformation tracking strategy using the template matching algorithm for dislocation estimation and coherent point drift algorithm, a point based non-rigid image registration algorithm, for the

estimation of the non-rigid component of the deformation. Template matching algorithm uses the correlation method for the tracking of the dislocation of the feature in the captured intra-operative images. This is computationally light and hence fast algorithm and gives the gross estimation of the position of the target. This helps in reducing the search space for the non-rigid deformation estimation in the second stage. CPD algorithm treats the alignment of two point-sets as a probability density estimation problem and also makes use of motion coherence theory for the smoothing of the displacement function. The proposed image processing techniques are formulated in this chapter. After the discussion and formulation of the template matching and CPD algorithm, a tracking method is proposed for the continuous and real-time tracking and treatment plan updating. The tracking algorithm proposed in this work exploits the temporal continuity of the brain deformation. Rather than register the first US image US_1 captured and the current image US_n for each estimation, the proposed algorithm utilises the transformation estimated till the previous estimation $T_{US}(n-1)$ and composes it with the deformation estimated between the US_{n-1} and US_n , $dT_{US}(n)$. The implementation, experimental setup and testing of this strategy is explained in Chapter 6.

CHAPTER 4. HYBRID CONTROL STRATEGY FOR NEUROSURGICAL ROBOTS- METHODOLOGY

For accurate treatment delivery in minimally or non-invasive neurosurgery robotic system, two components are crucial for the accurate delivery of treatment- 1) real-time and accurate brain shift estimation and 2) accurate positioning of the robot end-effector based on the update treatment plan. In the previous chapter, the author focused on the first component and proposed a strategy for the deformation estimation and real-time tracking of the target. The focus of this chapter is on the second component i.e., the accurate positioning of the robot once the target position is obtained.

Robotics was employed in medical arena after its success in industrial application. However compared to the industrial robots, accuracy, stability and other safety criteria are much more stringent in the case of medical robots especially surgical robots. This is because in case of surgical robots, human life is at stake. Also the operating room environment is unpredictable and dynamic. One of the ways to ensure the required performance by the robot for a given application is by devising a suitable control system. Control system is the brain of a robotic system. It ensures accurate and stable performance of a robot by predicting and compensating for errors.

In this work, we devise a control strategy for neurosurgical robotic system for fail-safe operation by ensuring accurate positioning of the surgical tool and stable operation. Three-layer hierarchical hybrid control architecture with a high-level supervisor, mid-level control and low-level control is proposed in this work. In the proposed hybrid controller, PID controller and Direct Model Reference Adaptive Controller (DMRAC) are the constituent controllers. In this chapter, we discuss and formulate the proposed control strategy. In the block diagram of a general neurosurgical robotic system shown in Figure 1.1, the thrust of this chapter is on the 'Controller' unit.

4.1 Proposed Treatment Protocol for Non-invasive Neurosurgery

The most important issues to tackle in a non-invasive neurosurgery are compensating for the intra-operative brain tissue deformation and accurately targeting the tumour. Depending solely on the pre-operative images for treatment would lead to inaccuracies as brain shift can make the pre-operative plan outdated. In this work, a dynamic control of the neurosurgical robot is proposed. The block diagram of the surgical protocol is shown in Figure 4.1.

Figure 4.1 Proposed treatment protocol for non-invasive robotic neurosurgery

In the first stage of the treatment, the surgeon studies the pre-operative images of the patient to understand the affected areas in the brain and the sensitive parts of the brain close to the tumour. The pre-operative images are generally taken using MRI or CT imaging modalities. A set of points on the tumour to be targeted are identified. The treatment point set must cover the entire volume of the tumour. The pre-operative planning stage is completed well in advance of the treatment stage. The control strategy developed in this work was tested on a HIFU-based neurosurgical robot, FUSBOT-NS. Hence, the treatment protocol discussed below is in the context of a HIFU-based surgery.

The size of a Grade II brain tumour (explained in Section 2.3) is typically 30mm in diameter and has a regular geometric shape, spherical ovoid or cylindrical. However, a HIFU lesion is cigar-shaped and of dimension 10-50mm in length and 1-5mm in diameter. Hence, due to the small size of the HIFU lesion, the HIFU focal zone has to be moved point by point throughout the volume of the tumour for complete ablation. There is a greater chance for recurrence of the

tumour if any part of it is left unablated. Generally in a 20mm by 20mm area, approximately 200 points are targeted in HIFU surgery. The path and sequence of the treatment points during the surgery is planned carefully in order to achieve minimum treatment time and also to avoid sensitive and critical regions in the brain. Three possible treatment protocols/trajectories are explained below and the schematic of the protocols are shown in Figure 4.2:

Adjacent points: In this protocol, the adjacent points are targeted one after another both in the transverse and the sagittal plane. However, this path sequence will prolong the treatment time. As explained in Section 2.4, HIFU ablates the targeted tissue by deposition of thermal energy thereby raising the temperature at that point to a temperature of 65 - 100°C in 5 - 20seconds to form a thermal coagulative necrosis. A treatment point close to the formed lesion cannot be targeted unless the lesion area cools down as its ablation can lead to cavitation effects. Hence, after the targeting of one treatment point, there is a waiting time of about 10-20seconds, time required for cooling down, before the ablation of the next point.

Distant points: In this protocol, in order to eliminate the waiting time between each treatment point, a treatment point away from the treated point, where the temperature is high, is targeted immediately without waiting for the cooling of the treated point. This way, the surgery can be completed faster and also as result, the amount of brain shift that occurs in the time between targeting two treatment points can be minimized.

Arbitrary points: This protocol is generally followed in the event of a surgeon intervention where it is important to decide which point needs to be targeted at that point of time rather than follow the pre-planned (during treatment planning) sequence of treatment points. This protocol may be used in the event where a critical region of the brain or a major blood vessel needs to be avoided or is close to the intended treatment point. Due to the surgeon's intervention, the treatment time will be longer and the path and sequence of the treatment will be unstructured.

Figure 4.2 Representation of the three treatment protocols in HIFU-based neurosurgery; red oval represents the ablated point and the arrow and associated number represent the next target point and sequence of treatment

In stage 2 i.e., the treatment stage, the pre-operative treatment plan is fed to the neurosurgical robotic system. During the initialization of the robot in the treatment stage, the patient's head and the robot, the intra-operative imaging modality (ultrasound imaging) and the patient's head and, the robot and the imaging modality are registered so as to establish a relationship among the robot co-ordinates, imaging modality co-ordinates and the target co-ordinates. After the initialization, the robot, which carries the surgical tool (X-ray, LINAC, HIFU), moves from one treatment point to the next as per the updated treatment plan to ablate the tumour at each point. The dynamic deformation tracking unit, continuously tracks the brain tissue deformation with the aid of the intra-operative images and updates the pre-operative treatment plan based in the current tumour position. The dynamic tracking unit registers the ultrasound scans performed during the surgery to obtain the current tumour position.

4.2 Motion Controller and Control Derivation

The primary focus of this work is the trajectory control of neurosurgical robots, which ensures accuracy and quick response time which is essential for the given application.

Requirements

Accuracy: A frame-based procedure has an accuracy of 0.8mm. Other than the mechanical inaccuracies, one of the major source of errors is from the imaging and image processing section of the system. For example, an ultrasound image has a resolution of only 0.2-0.3mm or a CT slice of 1.25mm introduces an uncertainty of approximately 0.625mm in the inferior/superior coordinates of the treatment volume. The aim of all neurosurgical robots is to achieve accuracy comparable to the frame-based system as it is considered the gold standard in target

localization techniques. However, as mentioned above the imaging system adds to the overall error in an image-guided non-invasive neurosurgical robot. In case of an open surgery, the accuracy of the surgeon is between 3 to 5mm [27]. The position estimation accuracy achieved in an image based surgical system is in the range of 1-2mm [8, 27]. Hence in order to achieve an overall accuracy of approximately 2mm, the positional accuracy of the robot must be below 0.2mm.

Response Time: In order to ensure accurate targeting of the tumour without affecting the surrounding tissues, it is important that the robot is able to track the deformations of the brain in a timely fashion. For normal tumour resection surgery, which takes about 6-8hours for completion, a total shift of 50mm (for larger lesions) is observed, which means an average shift of 0.594mm every 300seconds, approximate time taken for MI based rigid registration [8]. However, the use of a much faster registration algorithm can reduce the amount of shift that can happen between two tumour position updates.

In this section, the general purpose controllers to be used are discussed and formulated.

4.2.1 Proportional-Integral-Derivative Controller

The PID controller is the most popular controller adopted for various applications. Simplicity and ease of implementation are the main advantages of using this controller. This controller has been used as a part of the hybrid controller in one of the surgical robots developed by our research group and has shown good results [60].

PID control has a major disadvantage in that it cannot be used for applications where rapid disturbances and time varying parameter are expected. Also, the order of the system to be controlled must be low. The derivative term in the controller can cause large changes in the output even for a small amount of measurement or process noise. This poses a significant problem especially in robots working in medical environment which has rapid disturbances and time-varying parameters. For example, 1) dislocation and deformation of the brain tumour is unpredictable and dynamic. It has been observed that the brain morphology can change in less than sixty minutes without any surgical manipulation after the dura mater is opened [10]. 2)

The presence of human(s) in the working loop of the robot also contributes to the disturbances and changes in parameter.

Hence, a PID controller alone may not be able to provide the required accuracy and stability for the end-effector which performs the surgery but will be sufficient for the control of the base manipulator which is active only before the actual surgery. A general block diagram of the controller [97] is shown in Figure 4.3 where e is the error signal, u is the control signal, and K_p , K_i , K_d are the proportional, integral and derivative gains respectively.

Figure 4.3 Block diagram of a PID controller

$$T = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt}, \quad e(t) = d_r(t) - d_f(t) \quad (4.1)$$

Equation 4.1 is the torque equation for a PID controller where T is the torque output, $e(t)$ is the error signal, $d_r(t)$ and $d_f(t)$ represents the reference and the feedback signal respectively.

In order to negate or minimize the error and instability of the system in a dynamic environment when only the PID control is used, a control approach has to be implemented competitively or complementary to the PID controller. Broadly speaking, there are two approaches that can be used 1) Model-based controller, 2) Non-model based controller.

For a model-based controller, for example robust control, to be effective in its work, it requires an explicit knowledge of the dynamics of the system and also boundaries of the uncertainties. This is a drawback of the controller especially when used in applications where uncertainty boundaries cannot be defined and unforeseen changes occur in the system dynamic

parameters and input signals such as change in position and direction information. In neurosurgery, as shown earlier, the tissues deform in a very unpredictable manner

In the case of this research, as explained under Section 2.10, the change in tumour location due to deformations in the brain tissues is dynamic and not predictable. Deformations have to be constantly monitored and tracked. Hence the input to the robot is also unpredictable. In such circumstances, where exact modelling is not possible, a model-based controller cannot maintain sub-millimetre accuracy (the accuracy for various neurosurgical robots are listed in Table 2.2) which is required for neurosurgery. A non-model based controller like neural network controller or adaptive learning control, which is capable of automatically compensating for the unexpected changes in the parameters and input, would be suitable for such applications.

In neural network control, the controller learns about the inverse dynamics of the robot through the input and output signals and adjusts the connection weights using the learning algorithm. After learning, the performance of the controller in following the ‘taught’ trajectory will generally be good as the robot would be able to interpolate between the training data points, provided it had succeeded in learning the inverse dynamic model. But, the performance deteriorates if the desired trajectory is not what was ‘taught’ to the controller [98, 99]. The response of the network to input outside the range of the training data will always be suspect. Hence, such a controller would not be suitable for the given application as the environment is unstructured and the desired trajectory varies case by case and is not repetitive in nature.

4.2.2 Direct Model Reference Adaptive Controller (DMRAC)

Another alternative for non-model controller is the adaptive controller. When the environment is unpredictable or when it is not economical to exactly model the complete system, such a controller is useful. There are basically three types of adaptive controller: direct, indirect and composite [99]. In direct adaptive controllers, the controller reduces the tracking errors of the joint motion based on computed torque control. It updates its parameter based on the tracking error. This type of controller is simple in implementation and rejects the parameter disturbances inherent in adaptive control [99]. The disadvantage is that it requires acceleration

measurements and also requires taking the inverse of the estimated inertia matrix. The indirect method uses prediction errors on the filtered joint torques to estimate the parameters. This method is relatively complex algorithm especially correlation of the prediction error with the estimated parameter error. The composite method is a combination of both these techniques.

Considering the point-to-point trajectory required for tumour ablation, a direct model reference adaptive controller (DMRAC) would be suitable as it is a relatively easy to implement the controller and also high-speed adaptation is possible as the identification of the plant dynamic performance is not required [99, 100]. The block diagram of a simple direct model reference adaptive controller is shown in Figure 4.4. The goal of this controller is to manipulate the output of the plant to approach asymptotically the output of the given reference model, which is also a part of the controller. Here, the explicit model of the desired behaviour is used rather than the model of the plant and also the error in the plant and model output is used to update the control parameters [100].

Figure 4.4 A simple direct model reference adaptive system with single adjustable parameter; $y_M(t)$ and $y_P(t)$ represents the model and plant output respectively, $e_1(t)$ is the error between $y_M(t)$ and $y_P(t)$, $u(t)$ is the input to the plant, $k(t)$ is the single adjustable parameter, $v(t)$ is the measurable state variable [100]

The robustness of MRAC in the face of an incomplete plant model, dynamic parameter variations and physiological motions is demonstrated in the simulation of the control architecture proposed by Cortesao et al [74] for motion compensation in robot-assisted surgery. The architecture is based on dynamic models, operational space description, computed

torque techniques, discrete state space and stochastic design. Two separate active observers are used in the architecture, one for force control and the other for physiological motion compensation. The simulation results showed good force control under sinusoidal as well as non-sinusoidal physiological motion (Figure 4.5).

Figure 4.5 (a) Force response for a sinusoidal disturbance of 2Hz and amplitude 3N applied at 6s along x dimension, (b) Force response to a non-sinusoidal disturbance applied at the start [74]

The work explained in [101] compares the performance of an electric-hydraulic servo system with PID controller and with MRAC. Although, the application is described in the work for industrial purpose, it highlights the advantage of MRAC in circumstances where there are time varying parameters and disturbances. Figure 4.6 shows the graphical representation of the simulation results obtained in [101]. The positional accuracy of the hydraulic system was tested in this work in presence of oil temperature variation. PID gave a very poor performance and made the system unstable. However MRAC was performed well with an error less than 1.8% of the input. From the results it is evident that a PID controller gives a very poor performance and is not robust as the system had strong non-linear and time varying characteristic while MRAC shows much better performance.

DMRAC control formulation

In this section, the DMRAC controller formulation is described.

Choice of Reference Model

The choice of the order of the reference model, which the plant will be forced to follow, is an important step in the implementation of DMRAC. If the order is too high, the response will be

too slow and if the order is too low, it may cause excessive gains in the controller and as a result cause much higher accelerations in the joints than the desired level. For the end-effector of FUSBOT-NS, a second order model was chosen for each of the four actuated links.

Figure 4.6 (a) Step Response of MRAC and PID, (b) Step Response of PID controller for varying temperature(20-40°C), (c) Step Response of MRAC for varying temperature (20-40°C) [101]

State space representation of the reference model is given by,

$$\dot{x}_m(t) = A_m x_m(t) + B_m u_m(t) \quad (4.2)$$

$$y_m(t) = C_m x_m(t) \quad (4.3)$$

Since, medical robots deal with human patients it is desirable that there is no overshoot. Hence a critical damping ($\zeta=1$) chosen for the reference model so as to reduce the chances of joint overshoot. Since critical damping was chosen, the choice of natural frequency influences the

speed of response of the model to the inputs. The natural frequency of $\omega_n = 3$ was selected as the initial value. This gives a 90 percent rise time of 1second.

The reference model transfer function for the joints is:

$$\frac{y_m(s)}{u_m(s)} = \frac{\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} = \frac{9}{s^2 + 6s + 9} \quad (4.4)$$

where, y_m is the model output and u_m is the input to the model.

State space representation of the model transfer function would be:

$$\begin{aligned} \dot{x}_m(t) &= \begin{bmatrix} -6 & -9 \\ 1 & 0 \end{bmatrix} x_m(t) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u_m(t) \\ y_m(t) &= [0 \quad 9] x_m(t) \end{aligned} \quad (4.5)$$

Feedforward for Plant and Model

For a model reference adaptive controller to guarantee stability, it is important that the system satisfies the almost strictly positive realness (ASPR) condition. But in reality, most systems do not satisfy this criterion. So in order to satisfy the ASPR condition, a parallel feedforward is provided with the plant i.e., the input to the plant augments the plant output (See Figure 4.7). The addition of this feedforward around the plant greatly improves the stabilizability of the adaptive system [102]. One of the most widely used parallel feedforward is the PD controller $H(s) = K(1+s/s_0)$, which in parallel becomes, $H^{-1}(s) = K^{-1}/(1+s/s_0)$.

In order to ensure the stability of the plant any value for the gain K would be achieve the goal. However, it is desirable to use the value of the highest gain that maintains stability. This is because in parallel, the gain of $H^{-1}(s)$ would be really small and hence the output of the feedforward would be small as well and hence the augmented plant output will be more or less the same. The feedforward augmentation is defined as

$$\frac{R_p(s)}{U_p(s)} = \frac{D}{\tau s + 1} \quad (4.6)$$

$$\dot{s}_p(t) = A_s s_p(t) + B_s u_p(t) \quad (4.7)$$

$$r_p(t) = D_p s_p(t) \quad (4.8)$$

From the simulation results, the gain D was chosen as 5 and τ as 0.5. Hence, the plant feedforward would be,

$$\frac{R_p(s)}{U_p(s)} = \frac{5}{0.5s+1} \quad (4.9)$$

The state space representation of equation 4.9 is given by:

$$\dot{s}_p(t) = [-2]s_p(t) + [2]u_p(t) \quad (4.10)$$

$$r_p(t) = [5]s_p(t) \quad (4.11)$$

Although, addition of a plant feedforward helps in ensuring stability of the adaptive system, it increases the steady error. This problem can be alleviated the help of a feedforward around the reference model so as to minimize the model following error. The error due to the plant feedforward is bounding but never zero in steady state. The same approach as in the case of the plant feedforward is used here. A PD controller similar to the plant feedforward is provided in this case which is defined as,

$$\dot{s}_m(t) = A_s s_m(t) + B_s [u_p(t) - K_e(t)(z_m(t) - z_p(t))] \quad (4.12)$$

$$r_m(t) = D_p s_m(t) \quad (4.13)$$

From the simulation results, the gain D was chosen as 5 and τ as 0.5. Hence, the reference model feedforward would be,

$$\frac{R_m(s)}{U_m(s)} = \frac{D}{\tau s+1} = \frac{5}{0.5s+1} \quad (4.14)$$

The state representation would be

$$\dot{s}_m(t) = [-2]s_m(t) + [2]u_x(t) \quad (4.15)$$

$$r_m(t) = [5]s_m(t) \quad (4.16)$$

$$u_x(t) = u_p(t) - K_e(t)(z_m(t) - z_p(t)) \quad (4.17)$$

From equation 4.6,

$$z_p(t) = y_p(t) + r_p(t) = y_p(t) + R_p u_p(t) \quad (4.18)$$

where, $r_p(t)$ is the output of $R_p(s)$ acting on $u_p(t)$.

$$z_p(t) = y_m(t) + r_m(t) \quad (4.19)$$

where, $r_m(t)$ defined by equation 4.14.

Figure 4.7 shows the block diagram of the proposed model reference adaptive controller.

Figure 4.7 A general block diagram of direct model reference adaptive controller with plant and model feedforward

Adaptive law is defined by,

$$u_p(t) = K(t)r(t) \quad (4.20)$$

where,

$$K(t) = [K_e(t), K_x(t), K_s(t), K_u(t)] = K_p(t) + K_I(t) \quad (4.21)$$

$$r^T(t) = [z_m^T(t) - z_p^T(t), x_m^T(t), u_m^T(t)] \quad (4.22)$$

$$K_I(t) = (z_m(t) - z_p(t)) r^T(t) T \quad (4.23)$$

$$K_P(t) = (z_m(t) - z_p(t)) r^T(t) \bar{T} \quad (4.24)$$

$$T = T_I I_3 \quad (4.25)$$

$$\bar{T} = T_P I_3 \quad (4.26)$$

I_3 is the identity matrix of the order (3X3) and T_I, T_P are scalar.

4.2.3 Hybrid Supervisory Controller

A hybrid controller consists of a continuous system that is to be controlled, a family of parameterised controllers and a switching function. It is the interaction of the continuous and discrete dynamics that characterises a hybrid control structure [28]. The advantage of using a hybrid controller is that we can use more than one controller to maintain the performance level of the concerned system. In this work, we propose to use two different controllers i.e., PID controller and model reference adaptive controller, for the control of robotic neurosurgical systems. Figure 4.8 shows the block diagram of the proposed hybrid controller. The logic-based switcher switches from one controller to the other depending on the state of the system and the predefined strategy. The switcher can be a human operator (e.g. surgeon), an independent algorithm or a controller in the system [28].

Broadly speaking, a switching logic can come under two classes 1) non-estimator based and 2) estimator-based supervisor. The non-estimator based supervisor measures the tuning error and then issues a switching command. This type of supervisor is also known as the ‘pre-routed’ parameter tuner. It is only useful when the number of system parameters is small and it only deals with scheduling [28]. In the case of an estimator-based supervisor, the basic working principle is that it evaluates the performance of each constituent controller for the given task for the current state of the system [28]. It has scheduling and routing capabilities and hence is

expected to produce better results. In this research, an estimator-based supervisor is proposed as it chooses the controller based on the output estimate of each available controller for the given application at the given state of the system. The output estimation and comparisons are done in real time while the non-estimator based supervisor decides based on a predetermined route.

Figure 4.8 Block diagram of the hybrid controller proposed for neurosurgical robots

In this work, a hierarchical control scheme is proposed for the neurosurgical robotic system. Figure 4.9 shows the hierarchical hybrid controller proposed in this research for neurosurgical robots. It consists of three control layers 1) the high level supervisor, 2) the mid-level control and 3) the low-level control.

The high level supervisor is concerned with the decision making process of the neurosurgical robot. Some of the decisions taken by this control layer include

- 1) Event detection- The high level supervisor based on the information from the various modules in the system detects/predicts events such as a) failure of the robot, b) completion of ablation of the target point in the tumour, d) dislocation or deformation of the tissues, e) detection of a critical part of the brain close to the target and f) a command from the human operator. As and when an event is detected, appropriate instructions are issued to the lower layer by the high level supervisor.
- 2) Path planning is another task of this layer. When information of a dislocation of tissues or the target being too close to a sensitive region of the brain is received, the supervisor gives

instruction for the new target location or a new trajectory so as to avoid critical structures in the brain.

3) Controller selection- Based on the current state of the system one of the constituent controllers is selected. As was discussed previously, an estimator-based supervisor is used for this purpose.

Figure 4.9 Proposed hierarchical hybrid controller

The trajectory of the end-effector is considered in two parts- coarse positioning and fine positioning. Point-to-point motion of the end-effector as per the treatment plan, i.e., during targeting from one treatment point on the tumour to the next, comes under coarse positioning. In this case, the PID controller is used as the treatment plan movement is pre-planned and is a first order point-to-point motion. But during the surgery, the robot has to target the deforming target quickly and accurately. This task would come under fine positioning as active tracking of the target is needed and hence, the adaptive control will be used. In the presence of

uncertainties, the performance of PID will deteriorate and thereby affect the accuracy of the system. Hence for the control selection, the supervisor layer has to be actively monitoring the status of the surgery through its various inputs.

4) Failure detection/prediction- As mentioned earlier, medical robots have a very stringent safety criteria. For the safety of both the patient and the surgeon, it is important that, in the event of failure, the surgical robot fails safely without causing any injury or damage. This can be done by adding mechanical and software constraints. In the proposed control scheme, the high level supervisor constantly monitors the information from the internal sensors such as the joint position and torque sensors of the robot so as to detect or predict the chance of a failure. In the event of a failure, the system saves all the information about the status of the surgery and safely shuts down the robot i.e., the robotic intervention is directly interrupted and the robot is brought to a controlled halt. The surgeon is given the authority to override the computer supervision if deemed necessary, any time.

Mid-Level control has the task of switching among the constituent controllers of the hybrid controller based on the input from the higher control layer.

Low Level control is concerned with the position/trajectory control so as to move the robot along the trajectory specified by the high level supervisor. The controller selected by the high-level supervisor and 'connected to' by the mid-level control layer forms a closed feedback loop with the neurosurgical robot.

Hybrid Supervisory Controller derivation

A hybrid system is made up of mainly two sections- a continuous system which is to be controlled, called the plant and discrete system, the discrete event controller, which is in a feedback loop with the plant via an interface. The block diagram of a hybrid supervisory control is presented in Figure 4.10.

Continuous system/plant (FUSBOT-NS): Non-linear uncertain system is represented by a set of ordinary differential equations.

Discrete Event Controller (DEC)/Supervisor: the controller or supervisor is a discrete event system modelled as a deterministic finite automaton. The automaton is specified by: $S = (\tilde{S}, \tilde{X}, \tilde{R}, \delta, \phi)$, where

$\tilde{S}$ - set of states,

$\tilde{X}$ - set of plant symbols generated by the plant,

$\tilde{R}$ - set of controller symbols generated by the supervisor,

δ - state transition function, and,

ϕ -output function.

The working of the DEC is described as,

$$\tilde{s}[n] = \delta(\tilde{s}[n-1], \tilde{x}[n]) \quad (4.27)$$

$$\tilde{r}[n] = \phi(\tilde{s}[n]) \quad (4.28)$$

where $\tilde{s}[n]$, $\tilde{x}[n]$, $\tilde{r}[n]$ belongs to $\tilde{S}, \tilde{X}, \tilde{R}$ respectively. n refers to order of the symbols in the sequence.

Interface: An interface is required between the DEC and the plant as they understand different type of signals. The interface between the supervisor and the hybrid system converts the continuous signal from the plant to symbols which can be understood by the controller and similarly, symbols from the controller to continuous signals which is understood by the continuous plant. The plant symbols used and their conversion to continuous signals will be discussed in later in this chapter. The interface system consists of generator and actuator subsystem. The generator upon plant event, generate plant symbol to the supervisor. On the other hand, the actuator converts supervisor decision into input signal for the plant. The interface consists of two subsystems- the generator and the actuator.

The generator converts the continuous signal from the plant to a symbolic input for the controller (asynchronous). There are two steps to the working of the generator- 1) a mechanism to determine when a plant event has occurred so as to generate the plant symbol, 2) a mechanism to determine which plant symbol should be generated for the event that has

occurred. On the other hand, the actuator converts the supervisor decision (controller symbols) into input signal for the continuous plant.

Figure 4.10 Block diagram of the hybrid controller

The occurrence of a plant event is caused by the plant state trajectory crossing the pre-determined hypersurfaces in the plant state space. A hypersurface is the term which refers to the partitioning line that divides the plant's (FUSBOT-NS) set of state space into few regions. If the state trajectory crosses a hypersurface i.e., from one partition to another partition which has been pre-determined, the event occurs. The hypersurface state is specified based on the error data generated by experimental test with PID position controller and DMRAC controller and also based on various operational conditions such as in the event of initialization of the robot, coarse positioning of the end-effector, failure (mechanical or software) and human supervisor intervention.

The variation of the state variables of the hybrid control strategy is chosen to be steady state variation. In this variation, the value of the state variables at the end of one control section is used as the initial conditions for the following control section. The plant symbol is generated by the generator, in the interface, according to the following function:

$$\alpha_i : N(h_i) \rightarrow \tilde{X} \quad (4.29)$$

where, h_i for $i = 1, 2, \dots, m$ is the hypersurfaces specified by the designer of the system. $N(h_i)$ is the function that correlates each hypersurface with its plant symbol.

The sequence of the plant symbols is described as:

$$\tilde{x}[n] = \alpha_i(x(\tau_e[n])) \quad (4.30)$$

where $(\tau_e[n])$ is the time of the n^{th} plant event, with $\tau_e[0] = 0$.

The supervisor analyses each plant symbol that it receives via the interface and generates an appropriate controller symbol and passes it to the interface, which is then converted to a continuous signal (plant input) by the actuator in the interface. Between the plant symbol generation and the controller symbol generation, there is a time delay.

$$\tau_c[n] = \tau_e[n] + \tau_d \quad (4.31)$$

where, $\tau_c[n]$ is the time of the n^{th} controller symbol and τ_d is the total delay. This delay cannot be avoided for two reasons 1) the generator cannot detect an event until the state has crossed the hypersurface 2) it is possible (theoretically) that the plant will exhibit solutions that will switch between control policies infinite times in a finite period of time if there is no delay.

Once the plant symbol is received by the supervisor, the supervisor has to determine which controller is suitable for the next system states. The system, $\dot{x} = X(x, u, v, t)$, $y = H(x)$ with control input u , output y , with positioning error $[e_T \approx r - y]$ where r is reference point, is governed by a hybrid controller with an event driven logic switcher. The goal of the logic switcher is to change the controller (generating output $[\phi]$) in order to bring $e_T \approx 0$.

Let p_i is the i^{th} number of the plant event for $i = 1, 2, \dots, m$. p_i is a subset of a function of real, finite number P . X_{EP} is the state-space variable at p_i . For each $p_i \in P$, $e_{pi} \approx y_{pi} - y$ represents the p_i output estimation error. π_p denotes the normalized value of e_p , the performance signal, which is used by the supervisor to evaluate the potential performance of controller p . $\sum s$ denotes switching logic function determines σ based on the current value of π_p . The

estimator-based supervisor, from time to time when the plant event occurs, it picks for candidates' control signal $[v_p]$ whose corresponding performance signal π_p is the smallest among the π_{p_i} , for $[p_i \in P]$. Since the proposed hybrid controller has only two continuous controllers (PID and DMRAC) to be chosen it is relatively simpler and faster task than having many controllers. Since there are only two constituent controllers in the proposed hybrid supervisory controller, $\tilde{R} = \{\bar{r}_1, \bar{r}_2\}$, so the actuator provides two possible controller plant inputs, which is given by,

$$\gamma(r) = \begin{cases} 0, & \text{if } r = \bar{r}_1 \\ 1, & \text{if } r = \bar{r}_2 \end{cases} \quad (4.32)$$

Here, 0 denotes the DMRAC controller and 1 denotes the PID controller. Once the plant input is received the appropriate controller is chosen based on the supervisor's directions.

Smooth switching when a plant event occurs is very important for the overall performance of the system. If the performance signal π_p of both the PID controller and DMRAC are the same or very close in value then there is a high chance of switching to occur back and forth leading to jitter and chatter. In order to prevent such a problem, a simple hysteresis switching [29, 103-105] was employed. Using this method, switching from one controller to the other occurs only when performance signal of the controller out of the control loop is greater than the performance signal of the controller in the loop by a value h (where $h > 0$). Figure 4.11 shows the flowchart of the hysteresis switching method. In the developed controller, PID controller is considered the default controller and hence PID controller is used at the start of the robot operation. Later, based on the performance at each plant event, the best performing controller is switched into the control loop.

In this work, the value of h is set as 0.1 i.e., if the controller not switched in to the control loop has a performance signal π_p less than the sum of the performance signal of the controller in the loop and h ($h=0.1$), then switching of controller takes place. The switching process proposed in this work is continuous and smooth in nature. There is no halt in the system operation before switching to the new controller.

Figure 4.11 Flowchart for hysteresis switching

The proposed hybrid system recognizes eight plant events:

$$h_1 = x_1, h_2 = -x_1, h_3 = x_2, h_4 = -x_2, h_5 = x_3, h_6 = -x_3, h_7 = x_4, h_8 = x_5 \quad (4.33)$$

Symbols generated by the interface for each plant event are as follows:

$$\alpha_1 = \widetilde{x}_1, \alpha_2 = \neg\widetilde{x}_1, \alpha_3 = \widetilde{x}_2, \alpha_4 = \neg\widetilde{x}_2, \alpha_5 = \widetilde{x}_3, \alpha_6 = \neg\widetilde{x}_3, \alpha_7 = \widetilde{x}_4, \alpha_8 = \widetilde{x}_5 \quad (4.34)$$

$\widetilde{x}_1$ – denotes the initialization of the neurosurgical robot and also its positioning at the pre-defined home position before the start of the surgery.

$\neg\widetilde{x}_1$ - denotes the completion of the surgery. For this event, the robot is brought back to the home/ initial position from its current position before it is shut down.

$\widetilde{x}_2$ - denotes the gross positioning of the end-effector close to the patient's head via the base manipulator before treating the target points. This positioning is based on the pre-operative treatment plan and is performed at low speed.

$\neg\widetilde{x}_2$ denotes the completion of the gross positioning and transfer of control for the dynamic targeting of the lesion in the brain by the surgical tool attached to the end-effector, based on the input from the imaging system or human operator input.

$\widetilde{x}_3$ – denotes the event of failure of the imaging system. The supervisor pauses the neurosurgical robot till the imaging system failure is sorted out or a human operator takes over the surgery. This is done so as to ensure the safety of the patient as well the surgeon/operator monitoring the surgery.

$\neg\widetilde{x}_3$ - denotes the event where the faulty imaging system is functional again. In such an event, the surgery is resumed from the point it had paused its operation.

$\widetilde{x}_4$ - denotes the event where the human operator/surgeon takes over the operation of the neurosurgical robot. In such an event, the supervisor disables the input from the imaging system and hands over the operation and navigation of the robot to the human.

$\widetilde{x}_5$ - denotes event of an emergency shutdown initiated by the human operator. Such an event occurs when the safety measures included in the robotic system fails to detect a failure but is detected by the human operator. An emergency switch is provided to the surgeon, who is carefully monitoring the entire surgery, for him/her to shut down the robot in the event of such a failure.

The experimental setup and implementation results of the PID, DMRAC and the hierarchical hybrid controller are presented and discussed in Chapter 6.

4.3 Summary

A hierarchical hybrid controller with PID and DMRAC as the parameterised controllers was proposed as a control strategy. The proposed hierarchical control structure is a three layer structure- a High level supervisor, Mid-level and Low level control layer. The hybrid supervisory controller as well as its constituent controllers (PID and DMRAC) was formulated in this chapter. A performance estimation based Supervisor is used in the proposed controller. The smooth switching is ensured using a hysteresis based switching method. This method ensures that the controllers would be switched back and forth in event where the both performances are equal. Continuous back and forth switching can cause instability in the system or result in poor response. The proposed controller is tested on a HIFU-based neurosurgical robot, FUSBOT-NS.

The simulation and experimental results of the proposed controller testing is presented in Chapter 6.

CHAPTER 5. NEUROSURGICAL ROBOT AND SYSTEM MODELLING

The testing of the developed controller is performed on a representative HIFU-based neurosurgical robot, Focused Ultrasound Surgery Robot- Neurosurgery (FUSBOT-NS), developed by the Biomechatronics Group, Robotics Research Centre, NTU. The end-effector for this neurosurgical robot was specially modified by the author, keeping in mind required workspace, the strict accuracy and response time criteria discussed in Chapter 4. The chapter also discusses the kinematic and dynamic model of the designed end-effector structure is derived. A discussion on workspace of the robot is also presented. The focus of this chapter is on the 'Robot' block in the overall neurosurgery robotic system block diagram shown in Figure 1.1.

5.1 Design of FUSBOT-NS End-Effector

Almost all the medical robots use industrial robots for medical applications. However, since the safety criterion is extremely stringent for neurosurgery, a specially designed end-effector is needed. In this work, an end-effector was designed for non-invasive neurosurgical robots, particularly Focused Ultrasound Surgery Robot-Neurosurgery (FUSBOT-NS). The designed end-effector had four tasks/requirements- 1) Constraint degrees of freedom for safety reasons, 2) act as a carrier for the surgical tool and imaging probe, 3) enable positioning of the surgical tool throughout the entire treatment volume and 4) enable movement of the surgical tool along desired trajectory. In the following subsections 5.1.1 and 5.1.2, the design considerations for degrees of freedom and the mechanical configuration are explained. In this work, the developed controller is used to control only the end-effector part of FUSBOT-NS.

5.1.1 Degrees of Freedom

For the surgical tool to reach every point in the treatment volume and along desired trajectories, the manipulator would require six degrees of freedom. However, as mentioned previously, a constrained degree would minimize the safety concerns considerably [106]. An accepted design in medical robotics is to split the required DOF into two sections, one section provided by the base manipulator carrying the end-effector and the other section by the end-effector itself [3]. The base manipulator would be locked down once the end-effector is placed at the desired position and only the end-effector would be active during the surgery. This way

the active DOF is reduced, but the effective DOF would be six itself. For FUSBOT-NS, a similar manipulator design is used.

The end-effector of FUSBOT-NS is designed as a 3-DOF manipulator. The FUSBOT-NS base manipulator, which has three DOF, provides the gross positioning of the end-effector prior to the surgery. It is locked down after the positioning and the control is transferred to the end-effector to perform the surgery. Hence, the active DOF during the surgery is limited to three.

5.1.2 Serial or Parallel configuration

From Table 2.2, it is clear that almost all the neurosurgical robots are of serial type as well. Though serial robots have the advantage of large workspace, parallel manipulators have advantage on other factors which are important for surgical application like high strength to weight ratio, high stiffness, low inertia and have high speed motion capabilities and higher accuracy [107, 108] compared to serial manipulators. Also, for safety reason, large workspace can be a disadvantage as the chances of causing harm to surgeon or patient is high in the event of a malfunction. For all the advantages highlighted above, a parallel mechanisms chosen for the FUSBOT-NS end-effector.

5.1.3 Modified Parallel manipulator design

For the reasons discussed in Section 5.1.1 and 5.1.2, the end-effector manipulator of FUSBOT-NS is designed as a 3-DOF parallel robot. This manipulator has only two rotational and one translation axes. After the surgical tool, which is carried by the end-effector, is brought close to the cranial opening on the patient's head by the base manipulator, a suitable combination of pitch and yaw motion (rotation) and in-out motion (translation) would be enough for the tool to reach every point in the patient's brain.

The 3-DOF end-effector manipulator has four parallel links with translation axis (extension and retraction). The fourth link is redundant but actively driven, and was included so as to make the structure stable. The end-effector jig, which holds the surgical tool, is connected to a top plate via these four links and universal joints and the top plate is attached to the end of the base manipulator. The rotational motion of the jig is achieved by extending one link and retracting

the diametrically opposite one while the joints between the other two links and jig acts as the pivot point.

In the initial design of the end-effector manipulator, four linear actuators were used as the four parallel link of the robot. Firgelli L12 linear actuators [109] with 50mm stroke length and 0.1mm resolution were used for this purpose. Although, the design using these actuators was compact, the performance of the actuators was not suitable for the task of precise targeting in non-invasive neurosurgery. The tests showed that the resolution was only 0.7mm compared to 0.1mm stated in the datasheet [110]. Also, for load that used on the FUSBOT-NS end-effector, which was approximately 8 kgs, the Firgelli linear actuators showed slow and unstable performance. Hence, the motors as well as the driving mechanism for linear motion of the end-effector links was changed so as to test the controller against the accuracy and response time requirements stated in Section 4.2.

Two options were mainly considered for the design of the translational motion of the links of the end-effector mechanism (See Figure 5.1) - 1) Rack and pinion design, and 2) lead screw design. Rack and pinion design is simple in construction and requires fewer parts. However, it is difficult to achieve high precision and also there is the issue of vibration and noise during fast motion of the mechanism. It also suffers from the problem of high backlash and pitch error. On the other hand, lead screw design is compact, which is desirable feature for medical robots. It can provide very high precision and accuracy and less vibrations compared to rack and pinion design. However, lead screw design suffers from high wear and tear due to friction. The author opted for the lead screw approach for the FUSBOT-NS end-effector robot.

The selection of the motors is also of prime importance. The motor torque will determine the speed of operation of the end-effector in order to quickly respond to the input from the dynamic target tracking unit. Below, the load calculation for FUSBOT-NS is described.

Load calculation for selection of motor for FUSBOT-NS end-effector:

Mass of the FUSBOT-NS jig = 1.875 kgs

Mass of HIFU probes = $0.5 * \text{No. Of probes}$ = 1.5 kgs

Figure 5.1 (a) Rack and pinion design, (b) lead screw design that was adopted by the author

Mass of ultrasound imaging probe = 0.7 kgs

Mass of HIFU coupling medium = 1.5 kgs

Mass of drive components = 1.5kgs

Total Load = 7.075 kgs * 9.81 kg/sq. metre = **69.40 N**

This load is distributed among the four parallel links of the end-effector. However, as a safety allowance, for the calculation of the required torque of the motor we assume each motor has a load of half the total load.

Load for each motor= 69.4/2= **34.6N**

Required torque for the given load is given by:

$$T_{raise} = \frac{Fd_m}{2} \left(\frac{\mu \sec \alpha + \tan \lambda}{1 - \mu \sec \alpha \tan \lambda} \right)$$

$$T_{lower} = \frac{Fd_m}{2} \left(\frac{\mu \sec \alpha - \tan \lambda}{1 + \mu \sec \alpha \tan \lambda} \right)$$

Radius of the lead screw used= 0.005m

d_m , the mean diameter of the lead screw= 0.01m

For trapezoidal lead screw, the thread angle (α) would be 29 degrees and the lead angle of the helix (λ) would be 20 degrees.

Friction coefficient, $\mu = 0.2$, $F=34.6\text{N}$

Required Torque, $T= \mathbf{0.1059\text{ Nm}}$

Centre of Gravity of the end-effector

FUSBOT-NS end-effector is a symmetrical manipulator. The FUSBOT-NS jig (a brief description is given in Section 5.2) which holds the HIFU transducers and the coupling medium for the HIFU beam is also symmetrical. The lower half of the jig holds water (coupling medium) with the help of latex sheet at the open end. Figure 5.2 shows the schematic diagram of the end-effector for the calculation location of centre of gravity.

Figure 5.2 Schematic diagram for finding centre of gravity of the end-effector

The lead screws are symmetrically arranged and are all of the same material and dimensions. Mass of the lead screws= 1.5kgs.

Location of Centre of Gravity (CoG) of lead screws w.r.t Frame A= (0, 0, 150).

The FUSBOT-NS HIFU jig is cylindrical in shape. The mass of the jig, HIFU transducers and imaging probe= $1.875+1.5+0.7=3.975$ kgs. This is the mass of the upper half of the jig.

Location of its CoG w.r.t. Frame A= $(0,0,322.5)$.

The lower half of the jig is also cylindrical and is filled with water. The mass of the lower half=1.5kgs.

Location of the CoG w.r.t Frame A= $(0,0,367.5)$.

The origin of Frame A is taken as the datum to compute the moment of each mass.

Total moment= $1.5 \times 150+3.975 \times 322.5+1.5 \times 367.5=2058.2$ kg.mm.

Distance of the end-effector CoG from the Frame A origin=Total moment/ Total mass= $2058.2/(1.5+3.975+1.5)=295.082$ mm.

Location of CoG of end-effector w.r.t. Frame A= $(0,0, 295.082)$. The location of the CoG is well within the base of the end-effector and hence is a stable structure.

During the operation of the robot especially during the rotational motion of the end-effector, the CoG location can vary due to the presence of water in the jig. However, the tilt of the end-effector, as per required workspace (discussed in Section 5.3.2), is not more than 10 degrees. Hence the stability of the structure is not affected. In the unlikely scenario where the entire load of the coupling medium is carried by one motor, the load on that motor would be 41N. The required torque would be 0.1324Nm.

A motor which could generate torque equal to or greater than the required torque was selected. Faulhaber DC Micromotor (2224 024CR) with a continuous torque of 5mNm and gearhead of ratio 185:1 was selected as the motor for the application. The motor gives a torque of 0.4870 Nm, which is more than sufficient for the given application. The efficiency of the motor and the gearhead were 81% and 65% respectively.

5.2 FUSBOT-NS HIFU jig

The jig attached to the end-effector mechanism, in FUSBOT-NS, was specifically designed for HIFU-based neurosurgery by Biomechatronics group, NTU [111]. The end-effector jig of FUSBOT-NS has two parts – a water chamber and a transducer holder. These two parts are arranged in such way that the transducer holder moves within the water chamber as two concentric cylinders. The material used to fabricate the end-effector of the robot is Perspex, which has no effect on HIFU beams [111]. The water chamber with help of thin latex membrane holds the coupling medium (degassed water) which is required for efficient transfer of the HIFU energy to the intended site. A Sakagami seal is used between the transducer holder and the water chamber to prevent the coupling medium from leaking [111]. The transducer holder holds the HIFU probes.

In FUSBOT-NS, the transducer holder is designed to hold a multi-probe applicator consisting of three HIFU transducers. It also holds the ultrasound imaging probe for real-time intra-operative imaging. The imaging probe is held at the centre of the transducer holder. The transducers surround the imaging probe and are configured in such a way that the focus of each HIFU transducer converge to a single point. This gives an effective focal length of 72.5mm for the confocal point when using transducers with 80mm focal length. In order to avoid excessive movement of the coupling medium, linear vertical motion is given only to the transducer holder while the water chamber and coupling medium in the latex membrane remain stationary. Hence, two links are attached to the transducer holder and the other two to the water chamber. During surgery, the confocal point of the HIFU beams is positioned at the desired location on the tumour by controlling the end-effector using the three D.O.Fs.

5.3 System modelling

In this section, the mechanical modelling of FUSBOT-NS end-effector is presented.

5.3.1 Inverse Kinematic modelling

Robot arm kinematics is concerned with the analytical study of the geometry of motion of a robotic arm with respect to a fixed co-ordinate frame as a function of time without regard to the forces/moments that cause the motion [112]. Both the forward and inverse kinematics of

the end-effector was formulated. Denavit-Hartenberg method (D-H method) is most commonly used method for the derivation of the kinematic equations. However, the author used the geometric method for the purpose as it would be much simpler compared to the D-H method in the case of a parallel manipulator.

For the purpose of analysis, three co-ordinate frames are attached to the end-effector. The origin of the reference frame $A(x, y, z)$ is fixed on the fixed base which is the top plate, origin of co-ordinate frame $B_t(x, y, z)$ is fixed at the centre of the axis joining the two actuator joints on the transducer holder and, $B_w(x, y, z)$ is fixed at the centre of the axis joining the two actuator joints on the water chamber as shown in Figure 5.3.

Figure 5.3 Schematic diagram of the end-effector

The transformation of the moving jig and the fixed base can be defined by position vector $\mathbf{p}$ ($\mathbf{p}_t$ and $\mathbf{p}_w$) and rotational matrix ${}^A R_B$ of the jig. As mentioned earlier, the jig has three D.O.F. of which two are rotational. Hence the rotational matrix is defined by the pitch and yaw angles (euler angles) i.e., θ_x , which is the angle of rotation about the x axis and θ_y , which is the angle of

rotation about the y axis of the B co-ordinate frames. There is no rotation about the z axis for the jig ($\theta_z = 0$). The rotational matrix is defined as

$${}^A R_B = \begin{bmatrix} \cos \theta_y & \sin \theta_y \sin \theta_x & \sin \theta_y \cos \theta_x \\ 0 & \cos \theta_x & -\sin \theta_x \\ -\sin \theta_y & \cos \theta_y \sin \theta_x & \cos \theta_y \cos \theta_x \end{bmatrix} \quad (5.1)$$

Position Analysis

From Figure 5.3, the vector loop equation of each link is obtained as,

$$\mathbf{a}_i + d_i \mathbf{s}_i = \mathbf{p} + {}^A R_B {}^B \mathbf{b}_i \quad i=1, 2, 3, 4 \quad (5.2)$$

where, d_i represents the length of the i^{th} link,

$\mathbf{s}_i$ is the unit vector along the length of the i^{th} link,

$\mathbf{p} = \mathbf{p}_t$ for the links attached to transducer holder ($i=3, 4$) and,

$\mathbf{p} = \mathbf{p}_w$ for the links attached to the water chamber ($i=1, 2$).

From equation (5.2) we can deduce the length of the link as

$$d_i = |\mathbf{p} + {}^A R_B {}^B \mathbf{b}_i - \mathbf{a}_i| \quad i = 1, 2, 3, 4 \quad (5.3)$$

Velocity Analysis

To find the velocity at the joint B_i , we differentiate the right hand side of equation (5.2) with respect to time,

$$\mathbf{v}_{bi} = \mathbf{v}_p + \mathbf{w}_p \times \mathbf{b}_i \quad i = 1, 2, 3, 4 \quad (5.4)$$

where $\mathbf{v}_{bi}$ is the linear velocity at B_i ,

$\mathbf{v}_p$ is the linear velocity at $\mathbf{p}$,

$$\mathbf{b}_i = {}^A R_B {}^B \mathbf{b}_i,$$

$\mathbf{w}_p$ is the angular velocity of the moving jig about $\mathbf{p}$, $\mathbf{w}_p = \begin{bmatrix} \dot{\theta}_x & \dot{\theta}_y & 0 \end{bmatrix}$

The parallel links used in the end-effector manipulator consists mainly of two parts –1) the screw and 2) the cylinder (hollow), which moves along the screw up/down. The screw is coupled to the motor, which is in turn attached to the fixed base and the cylinder moves up and down along the screw. There are no rotational motions for the links.

The velocity at the centre of mass of the screw is zero as there is no motion. The velocity at the centre of mass of the cylinder is equal to the z-component of the velocity at link joint B_i .

$\mathbf{v}_{1i} = 0$; $\mathbf{v}_{2i} = [0 \ 0 \ v_{bi,z}]^T$; subscript '1' denotes the screw of the i^{th} link and '2' denotes the cylinder of the i^{th} link.

Acceleration Analysis

We can obtain the acceleration at link joint B_i by taking the time derivative of equation (5.4),

$$\dot{\mathbf{v}}_{bi} = \dot{\mathbf{v}}_p + \dot{\mathbf{w}}_p \times \mathbf{b}_i + \mathbf{w}_p \times (\mathbf{w}_p \times \mathbf{b}_i) \quad (5.5)$$

where $\dot{\mathbf{v}}_{bi}, \dot{\mathbf{v}}_p$ are the linear accelerations at B_i and P respectively and $\dot{\mathbf{w}}_p$ is the angular acceleration at P .

$$\dot{\mathbf{w}}_p = \begin{bmatrix} \ddot{\theta}_x & \ddot{\theta}_y & 0 \end{bmatrix}.$$

The acceleration of the screw of the i^{th} link is zero and that of the cylinder will be the z-component of the acceleration at B_i ,

$$\dot{\mathbf{v}}_{1i} = 0; \dot{\mathbf{v}}_{2i} = \begin{bmatrix} 0 \\ 0 \\ \dot{v}_{bi,z} \end{bmatrix} \quad (5.6)$$

5.3.2 FUSBOT-NS End-Effector Workspace

A Grade II brain tumour is approximately 30mm in diameter and geometrically regular in shape i.e., spherical, ovoid or cylindrical [32]. The dimensions of a HIFU lesion are of the order 10-50mm in length and 1-5mm in diameter [43] depending on the exposure time and intensity of the HIFU beam. The lesions are normally much smaller than the dimensions of the tumour. So during treatment, the trajectory of the HIFU beam focus should be such that the lesions fill the volume of the tumour completely. Any unexposed or remaining part of the tumour after the surgery can lead to recurrence of the tumour.

Figure 5.4 Schematic representation of HIFU application via craniotomy [113]

For a HIFU applicator (single probe, multi-probe or phased array) of aperture 80mm and focal length of 100mm, a craniotomy of 50.8mm diameter would be required so as to target a tumour at a depth of 63.5mm from the skull. It is through this hole in the skull that the HIFU beam should target the tumour. With the help of the three degrees of freedom that the end-effector manipulator has, it is possible to bring the focus of the HIFU beams to every treatment point as per treatment plan. The trajectory of the end-effector has to be planned dynamically so as to track the deformation in the tumour caused by the HIFU ablation and also to ensure that critical regions and blood vessels in the brain are avoided.

The pitch motion of the end-effector will move the HIFU focus along the sagittal plane of the tumour and the yaw motion moves it in the transverse plane. The translation motion of the end-effector helps to adjust the depth at which the lesion is created. Combining these three motions will enable us to target points in 3-D space. The workspace constraints for the end-effector are [111]:

- 1) Axial motion of 10mm.
- 2) Pitch motion of 6 to 10 degrees
- 3) Yaw motion of 6 to 10 degrees

These workspace specifications are fitting in order to bring the focus to every point in the tumour in the brain through the craniotomy so as to ablate the tumour completely. From Figure 5.3, the position vector of the FUSBOT-NS end-effector point can be given as,

$\mathbf{p}_T = \mathbf{p} + {}^A\mathbf{R}_B \mathbf{p}_T$, where $\mathbf{p}_T$ is the position vector of the end-effector end point (HIFU focus) with respect to frame **A**, $\mathbf{p}$ is the position vector of the frame **B**, ${}^A\mathbf{R}_B$ is the rotation matrix of the jig and ${}^B\mathbf{p}_T$ is the position vector of the end-effector point with respect to frame **B**.

Using the equation of the position vector of the end-effector point was plotted using MATLAB software (Figure 5.6). Given the length of the lead screw, the angle of rotation about X and Y axis (pitch and yaw angle) can be computed using simple geometric method. From the schematic diagram shown in Figure 5.5, $\theta = \arcsin(((d1-d2)/2)/|\mathbf{b1}|)$ where $d1$, $d2$ are the length of the limb (lead screw) attached to the water chamber, $\mathbf{b1}$, $\mathbf{b2}$ are the position vector of the limb joints on water chamber w.r.t. the frame **B**, θ is the angle of rotation about Y axis of frame **B** due to the movement of the lead screws. The same method can be used to calculate the angle of rotation about X axis of frame **B** due to the movement of lead screw attached to the transducer holder.

Figure 5.5 Schematic diagram showing rotational motion of end-effector due to lead screw motion

Figure 5.6 Workspace of the end-effector- Axial motion of 10mm, pitch and yaw motion of 6 to 10degrees

5.3.3 Inverse Dynamic modelling

The dynamic modelling of a robot arm is concerned with the mathematical formulations of the equations of the robot arm's motion [112]. The equations of the robotic arm motion describe the dynamic behaviour of the robot. Various methods like Lagrange-Euler, Newton-Euler or d'Alembert principle have been adopted for the formulation of the dynamic behaviour. Any of the aforesaid methods can be used for the purpose as the equations obtained are equivalent of each other. However, the structure of the equations will be different as the objective of each method (faster computation, to facilitate control analysis or improvement of simulation) is different.

The formulation based on the generalized d'Alembert's principle provides a set of explicit equations of motion which is very useful for state space control analysis. Also it identifies very clearly the contributions of the translational and rotational motions of the links [112]. This method has also shown to be more efficient and useful for the real time control of parallel manipulators. In this work, we used the methodology proposed by Tsai [108, 114] using d'Alembert's principle and link Jacobian matrices to derive a compact form of the dynamic equations.

Manipulator and Link Jacobian Matrices

Finding the manipulator and link Jacobian matrices is an important step in the formulation of the equations using d'Alembert's principle. We can rewrite equation (5.4) in matrix form as

$$\mathbf{v}_{bi} = \mathbf{J}_{bi} \dot{x}_p, \quad (5.7)$$

$$\text{where, } \mathbf{J}_{bi} = \begin{bmatrix} 0 & b_{iz} \\ 0 & 0 \\ 1 - b_{ix} \end{bmatrix} \text{ and } \dot{x}_p = \begin{bmatrix} v_{pz} \\ w_{py} \end{bmatrix} \text{ for } i = 1, 2 \text{ and,}$$

$$\mathbf{J}_{bi} = \begin{bmatrix} 0 & 0 \\ 0 - b_{iz} \\ 1 & b_{iy} \end{bmatrix} \text{ and } \dot{x}_p = \begin{bmatrix} v_{pz} \\ w_{px} \end{bmatrix} \text{ for } i = 3, 4.$$

The rate of change of length of the links can be given as,

$$\dot{d}_i = J_{bi,z} \dot{x}_p, \quad J_{bi,z} \text{ is the third row of the } J_{bi}.$$

The equation for the four links can be written in matrix form as,

$$\dot{q}_w = \begin{bmatrix} \dot{d}_1 \\ \dot{d}_2 \end{bmatrix} = \begin{bmatrix} 1 & -b_{1x} \\ 1 & -b_{2x} \end{bmatrix} \begin{bmatrix} v_{pz} \\ w_{py} \end{bmatrix} = J_p \dot{x}_p \quad (5.8)$$

$$\dot{q}_t = \begin{bmatrix} \dot{d}_1 \\ \dot{d}_2 \end{bmatrix} = \begin{bmatrix} 1 & b_{3y} \\ 1 & b_{4y} \end{bmatrix} \begin{bmatrix} v_{pz} \\ w_{px} \end{bmatrix} = J_p \dot{x}_p \quad (5.9)$$

J_p is the *manipulator Jacobian matrix*.

We can rewrite equation (5.6) as,

$$\mathbf{v}_{1i} = \mathbf{0}; \mathbf{v}_{2i} = \begin{bmatrix} 0_{1 \times 2} \\ 0_{1 \times 2} \\ J_{bi,z} \end{bmatrix} \dot{x}_p \quad (5.10)$$

The links have no rotational or translational velocity components along the x and y axis.

$$\dot{x}_{1i} = \begin{bmatrix} v_{1i,x} \\ v_{1i,y} \\ v_{1i,z} \\ w_{1i,x} \\ w_{1i,y} \\ w_{1i,z} \end{bmatrix} = \mathbf{0} \quad (5.11)$$

$$\dot{x}_{2i} = \begin{bmatrix} v_{2i,x} \\ v_{2i,y} \\ v_{2i,z} \\ w_{2i,x} \\ w_{2i,y} \\ w_{2i,z} \end{bmatrix} = \begin{bmatrix} 0_{1 \times 2} \\ 0_{1 \times 2} \\ J_{bi,z} \\ 0_{1 \times 2} \\ 0_{1 \times 2} \\ 0_{1 \times 2} \end{bmatrix} \dot{x}_p = J_{2i} \dot{x}_p \quad (5.12)$$

J_{2i} is the *link Jacobian matrix*.

Dynamics

The dynamics equation was formulated by the d'Alembert's principle or the principle of virtual work [112, 115] which states that:

For any body, the algebraic sum of externally applied forces and the forces resisting motion in any given direction is zero.

The goal is to determine the input forces required to achieve the desired trajectory of motion for the end-effector.

$$F_p = \begin{bmatrix} f_p \\ n_p \end{bmatrix} = \begin{bmatrix} f_e + m_p g + m_p \dot{v}_p \\ n_e + {}^A I_p \dot{w}_p + w_p x({}^A I_p w_p) \end{bmatrix} \quad (5.13)$$

where, F_p is the resultant and applied forces and f_e is the external force acting at $\mathbf{p}$ and n_e is the external moment acting at $\mathbf{p}$.

For the actuating joints of the limbs on the water chamber,

$$\begin{aligned} f_e &= m_p \dot{v}_{b1,z} \hat{k} + m_p \dot{v}_{b2,z} \hat{k} \\ n_e &= {}^B b_1 x(m_p \dot{v}_{b1,z} \hat{k}) + {}^B b_2 x(m_p \dot{v}_{b2,z} \hat{k}) \end{aligned}$$

For the actuating joints of the links on the transducer holder,

$$\begin{aligned} f_e &= m_p \dot{v}_{b3,z} \hat{k} + m_p \dot{v}_{b4,z} \hat{k} \\ n_e &= {}^B b_3 x(m_p \dot{v}_{b3,z} \hat{k}) + {}^B b_4 x(m_p \dot{v}_{b4,z} \hat{k}) \end{aligned}$$

$$g = 9.81 \hat{k}$$

${}^A I_p = {}^A R_B {}^B I_p {}^B R_A$, is the mass moment of inertia taken about $\mathbf{p}$ with respect to the fixed frame A.

In the case of the links/actuators, no external forces other than the gravitational force act on them. The resultant force acting on the cylinder and screw of the links is given as:

$$F_{1i} = \begin{bmatrix} f_{1i} \\ n_{1i} \end{bmatrix} = \begin{bmatrix} 0_{2 \times 1} \\ m_{1i} g \\ 0_{3 \times 1} \end{bmatrix} \quad (5.14)$$

$$F_{2i} = \begin{bmatrix} f_{2i} \\ n_{2i} \end{bmatrix} = \begin{bmatrix} 0_{2 \times 1} \\ m_{2i} g + m_{2i} v_{2i,z} \\ 0_{3 \times 1} \end{bmatrix} \quad (5.15)$$

Equations of motion

The principle of virtual work for a parallel manipulator can be written as [114]

$$\delta q^T T + \delta x_p^T \hat{F}_p + \sum_i \delta x_i^T \hat{F}_i = 0$$

From the above equation, for the end-effector we get

$$\delta q_w^T T_{1,2} + \delta x_p^T \hat{F}_p + \sum_{i=1 \text{ to } 2} \delta x_{2i}^T \hat{F}_{2i} = 0 \quad (5.16)$$

$$\delta q_t^T T_{3,4} + \delta x_p^T \hat{F}_p + \sum_{i=3 \text{ to } 4} \delta x_{2i}^T \hat{F}_{2i} = 0 \quad (5.17)$$

$T_{1,2}$ and $T_{3,4}$ represent the vector of input forces exerted at the actuated joints of link 1&2 and 3&4 respectively.

The virtual displacements must be compatible with the kinematic constraints determined by the joints. For the end-effector parallel manipulator we have,

$$\delta x_{1i} = J_{1i} \delta x_p = 0 \quad (5.18)$$

$$\delta q_w = J_p \delta x_p \quad (5.19)$$

$$\delta q_t = J_p \delta x_p \quad (5.20)$$

$$\delta \mathbf{x}_{2i} = J_{2i} \delta \mathbf{x}_p \quad (5.21)$$

($\delta \mathbf{x}_{1i}$ does not appear in (5.16) and (5.17) because there is no motion for the screw of the links.)

Substituting equations (5.19), (5.20) and (5.21) in equation (5.16),

$$\delta \mathbf{x}_p^T (J_p^T T_{1,2} + \mathbf{F}_p + \sum_{i=1}^2 J_{2i}^T \mathbf{F}_{2i}) = 0 \quad (5.22)$$

Equation (5.22) is true for all $\delta \mathbf{x}_p$. Hence,

$$J_p^T T_{1,2} + \mathbf{F}_p + \sum_{i=1}^2 J_{2i}^T \mathbf{F}_{2i} = 0 \quad (5.23)$$

$$T_{1,2} = J_p^{-1} (-\mathbf{F}_p - \sum_{i=1}^2 J_{2i}^T \mathbf{F}_{2i}) \quad (5.24)$$

Similarly, from equation (5.17) we get

$$T_{3,4} = J_p^{-1} (-\mathbf{F}_p - \sum_{i=3}^4 J_{2i}^T \mathbf{F}_{2i}) \quad (5.25)$$

Equations (5.24) and (5.25) represent the dynamic model for the end-effector of FUSBOT-NS.

5.3.4 Inverse Dynamics Simulation

Based on the derived inverse dynamic solution, a MATLAB code was written and executed. The dynamic solution of the end-effector for required torque was performed without taking into account the effect of the degassed water and latex membrane holding the water.

The force required for both the translational motion of the transducer holder and the pitch and yaw motion of the end-effector jig were obtained through this simulation.

Understanding the forces required to move the end-effector along the desired trajectory is very important when designing a controller. The most commonly used trajectories, pitch, yaw and axial (of transducer holder) motion, were simulated and the required forces are plotted in Figure 5.7 and Figure 5.8.

In Figure 5.7, we can see that the torque required by the actuators attached to the transducer holder (TH) (T3 and T4) vary from -19N to 10N as it oscillates the TH ± 5 mm from the zero position. Torque T1 and T2 remains unchanged at -5N which is needed to support the weight.

Figure 5.7 Forces required for the axial motion

Figure 5.8 Forces required for the rotational motion

In Figure 5.8, the torque required by the actuators to perform the pitch and yaw rotations are shown. During rotation, two actuators attached to TH will move equal distance in opposite directions. Hence the torque required by one actuator will increase while torque required for the other actuator will decrease. The torque requirement for the actuators attached to the water chamber varies in the same way.

5.4 Summary

The controller is tested on a representative neurosurgical robot developed the Biomechatronics group, Robotics Research Centre, NTU. A two part structure is used for the robot- base manipulator and the end-effector. The base manipulator provides the approximate positioning of the end-effector and is locked down, while the end-effector will be active during the surgery. This is done to limit the DOF of the robot so as to reduce the risk of injury. The design of the end-effector as a 3-DOF parallel manipulator is explained in this chapter. A lead screw design is used for the driving the parallel links of the end-effector. The torque calculation is presented in this chapter. The inverse kinematic and dynamic modelling of the designed structure was also derived and executed in this chapter by the author. Using the kinematic equations, the workspace of FUSBOT-NS end-effector was also presented in this chapter.

CHAPTER 6. CONTROL STRATEGY FOR NEUROSURGICAL ROBOTIC SYSTEMS- RESULTS AND DISCUSSION

A dynamic deformation tracking algorithm was presented in the Chapter 3. The deformation tracker used a computationally fast template matching algorithm for the gross tumour position estimation and a point-based non-rigid Coherent Point Drift (CPD) image registration for the fine deformation estimation. The tracking algorithm was devised as an incremental estimation by exploiting the temporal continuity of brain deformation. In this chapter, the experimental setup for the testing of the deformation tracker is explained and the experimental testing of the tracker and results are discussed.

In Chapter 4, a three-level hierarchical hybrid controller was proposed and formulated for non-invasive neurosurgical robots. In the control architecture the first layer which is the high level supervisor is the decision making level. Based on the inputs from various sources such as the imaging system, human operator/surgeon, the robot sensors and so on, the supervisor decides on the course of action to ensure a safe operation. The mid-level layer is more like an interface between the supervisor and the neurosurgical robot and the low level control ensures the accurate and timely execution of the supervisor layer decision. In this chapter, the experimental setup used for the testing of the hybrid supervisory controller is presented. The simulation and experimental test of the controller and its results are presented and discussed. The representative robot, FUSBOT-NS, on which the control is tested is presented and modelled in Chapter 5.

6.1 Intra-operative Brain Tissue Deformation- Experimental setup, Results and Discussion

In the following subsections, the experimental setup used for the testing of the dynamic deformation tracker formulated in Chapter 3 is explained followed by the presentation and discussion of the results obtained in these tests.

6.1.1 Experimental Setup

The schematic of the experimental setup is shown in Figure 6.1. A 3.5MHz convex phase-array ultrasound probe was used for the online monitoring of the target. Two ultrasound images taken at different points of time during the testing were registered. CCD camera imaging was used along with the US imaging modality for the purpose of benchmarking.

Figure 6.1 Schematic diagram of experimental setup for testing-Template matching and CPD algorithm

A skull phantom was fabricated so as to simulate the clinical scenario. The material used for its fabrication is Perspex, which has US imaging properties close to that of the human skull [111] and also the dimension were chosen based on the average human skull dimensions of 22x15x18cm. The skull phantom is made transparent so that the target is visible in the CCD camera images. An opening was made on one side of the skull phantom to mimic craniotomy, and thus provide a clear acoustic window for use of an ultrasound probe. The image processing unit performs all the computation tasks for the estimation of the dislocation and deformation of the tissue phantom. The information from this unit can be used by the surgeons or fed to a robotic controller for the accurate targeting of the tumour. A picture of the experimental setup is shown in Figure 6.2.

An ultrasound phantom of the brain tissue and target was prepared by using a plastic ball (27mm in diameter) as a target while embedding it in a solidified jelly made from commercially

available agar agar powder. This phantom was prepared so as to simulate a scenario where the tumour is inside the brain soft tissue. A clear (translucent) jelly was used so that the embedded target (ball) would be visible in CCD camera images as well. The target phantom is shown in Figure 6.3. A motorized jig, shown in Figure 6.2, was used for providing a linear motion to the target phantom for the testing of the template matching algorithm. The ultrasound images of the target were grabbed at a rate of 13 frames per second. A image grabber developed by the author, using C++ Microsoft Foundation Class and Matrox Imaging Library (MIL) 8 [116], was used for grabbing the images. The images were saved in the bitmap file format.

Figure 6.3 shows the target images captured using the US probe and CCD camera respectively. MATLAB R2007b [117] was used for the implementation of the template matching and CPD algorithm and other image processing tasks. An Intel Pentium 4, 2 GHz computer was used for the implementation of the algorithms.

Figure 6.2 (a) Experimental setup for imaging the phantom, (b) Skull phantom fabricated using Perspex as material

6.1.2 Template Matching Algorithm- Results and Discussion

For the purpose of testing, the target ROI is first identified by the user manually in current image at the start of the tracking. Based on the selected template, the program automatically

reads the acquired images and identifies the target in each of them based on the grayscale value correlation. The co-ordinates of the centroid of the target object is computed and plotted. Thus, giving updated information of the position of the target.

Figure 6.3 (a) US image of the target inside the skull phantom, (b) CCD image of the target inside the skull phantom

In this set of experiments, a linear movement of only 40mm (due to space constraints in the skull phantom), in the direction of the gravity, was given to the tissue phantom with the help of the motorized jig. The motorized jig was controlled using a PID controller. The motion error was tested prior to the tracking algorithm. The jig was tested for very slow speed of 0.5mm/second as brain shift is also a very slow phenomenon. An error of 0.17mm was observed in the linear motion of the jig.

Figure 6.4(a) shows the change in the y co-ordinate of the centroid of the target, tracked by US imaging, as it moves down and then up by 40mm. Figure 6.4(b) shows the displacement of the target from its initial position tracked using US imaging. The displacement of the target was computed based on the pixel size of the ultrasound image viz., 0.3mm. A distance of 40.44mm was computed as the distance travelled by the target along the y axis. The slight error of 0.44mm, above the distance of 40mm that the target actually moved, can be attributed to the poor resolution of the US images and also error in calculating and locating the centroids.

Figure 6.4 (a) Change in y co-ordinates of the centroid of the moving target inside the skull phantom over time; tracking was done using US imaging, (b) Distance moved by the target over time

Figure 6.5 shows the change in the co-ordinates of the centroid of the target in the CCD images as the target moves down and then up by 40mm. The movement is linear and along the y axis. Figure 6.5(a) shows the change in the y co-ordinate as the target moves. The computed value of the distance travelled down and then up along the y axis is 39.5mm, which is approximately equal to the displacement given to the target using the motorized jig (40mm).

Figure 6.5 Tracking was done using CCD imaging- (a) Change in y co-ordinates of the centroid of the moving target inside the skull phantom over time, (b) Distance moved by the target over time

Template matching algorithm for the tracking of the target was found to be accurate and also fast. For real time applications, such as neurosurgery, computation time is a very critical factor.

6.1.3 CPD algorithm- Results and Discussion

Figure 6.6 (a) Original US image, (b) US image after filtering using Perona-Malik filter

Segmentation: Boundary tracing algorithm was used in order to segment the target from the ultrasound images. The boundary is then converted to a set of points for the registration algorithm to act upon. Ultrasound images are of very low resolution and very noisy. Hence it was difficult to perform automatic segmentation. In order to alleviate the problem of noise, a non-linear diffusion filter, Perona-Malik filter [8, 118], was used on the image as a pre-processing step. This filter has been shown to be effective in reducing the speckle noise and at the same time maintaining the boundary of the regions of interest [8]. The result of filtering can be observed in Figure 6.9. The use of low pass filters or linear diffusion filters would give better noise elimination but, only at the cost of blurring of the edges [118, 119], which is not desirable in our case as boundary of the feature (tumour) is required for registration.

Figure 6.7 US image of the deformed target

Non-rigid registration: A second phantom, with a deformed plastic ball (Figure 6.7) embedded in it, was made and imaged using the same setup as described above. The CPD algorithm was used to register the un-deformed target with the deformed target. After the registration, the error between the newly obtained transformed point set is compared with the point set from the deformed target so as to compute the registration error and thereby establish the efficacy of using the CPD algorithm. The computation time required for the registration is also noted. Figure 6.8(a) shows the point set of the traced boundaries of the un-deformed and the deformed target placed on top of each other. λ and β were set as 3 and 2 respectively and w , the weight for noise and outliers as 0.1. The point sets X (red points) is 928×2 points and Y (blue points) is 923×2 points. Here Y , which is point set from the undeformed target, is registered to X , which is the point set from the phantom with deformed target. Figure 6.8(b) shows the registered Y point set. Based on the correspondence between the two sets of points, the root mean square distance was measured. An error 0.429mm was observed in this trial. The registration took about 1minute and 58.6seconds to complete. Similarly, 11 other tests with different sets of images were performed. The computation time and the after and before registration errors are shown in Table 6.1. Since the computation time was depended on the configuration of the computer on which the algorithm was tested and also on the background applications running on the computer, two trials were conducted for each image set in order to neutralise the effect of the background applications.

Figure 6.8 (a) Overlapping Unregistered point sets X (Red) and Y (Blue), (b) Y registered to X using CPD algorithm

Table 6.1 Computation time and errors before and after CPD registration

Point Set	No. of points	Computation time (seconds)		p2p error before	p2p error after
		trial 1	trial 2	(mm)	(mm)
1	923	122	115.2	1.65	0.429
2	923	165	106.5	3.03	0.785
3	923	60.12	52.55	7.767	3.305
4	713	61.5	57.26	6.889	4.582
5	976	40.85	36.68	13.99	2.55
6	1080	77.52	72.59	6.88	2.47
7	978	165.6	115.3	2.369	0.58
8	923	112.8	108.3	1.419	0.374
9	831	33.09	33.17	6.11	3.71
10	831	129.19	129.19	8.476	2.83
11	915	37.56	38.17	0.341	0.254
12	915	48.6	66.1	6.495	1.495

In these 12 tests, an average error of 1.94mm and maximum error of 4.582mm and, an average computational time of approximately 1minute 12.7seconds was observed. From the experiments, it was observed that the error in the final registered point set had a strong positive correlation to the initial error i.e., the amount of deformation before registration. A correlation of 0.7 was computed from the data obtained from the trials (See Figure 6.9).

Figure 6.9 Correlation between point-to-point error after and before registration

If only a part of the desired feature is present in ultrasound image, the registration error will be high (Point set 2, 3, 9 in the above figure). This can happen in ultrasound imaging due to ultrasound shadowing or due to ultrasound speckles [24]. During registration, CPD algorithm

succeeds in maintain the integrity of the shape and structure of the point set even though, there was heavy deformity in the template point set. This is because of the motion coherence constraint imposed on the transformation from the initial position to the final position whereby points close to each other move coherently. Figure 6.10 shows the template and reference point sets (Point Set 3) before and after registration.

Figure 6.10 Partial feature in US images: Registration of point set 3

For a given computer configuration, the time of computation depends on the number of points in the point sets and also on the level of deformation. Although the average computation time for CPD was just above a minute, computation for some of the point set went more than 2minutes (Point sets 1,2,7,10). In order to speed up the computation, we introduced a down sampling factor to the number of points in the point sets after the segmentation. From our trials it was seen that this helped in reducing the computation time drastically by factor of 5 to 9. We tested the algorithm with a down sampling factor of $\frac{1}{2}$ and $\frac{1}{4}$. The comparison of their computation times are shown in Figure 6.11 (data table in APPENDIX A).

Figure 6.11 Comparison of computation time between full, 1/2 and 1/4 point set

With the use of a more powerful processor and also with use of parallel computing, the computational time can be further improved. However, the down sampling the point sets increased the registration error compared to the full point sets. The average registration error for registration with $\frac{1}{2}$ down sampling was 2.18mm and that of $\frac{1}{4}$ down sampling was 2.25mm. The comparison of the errors of registration between the full point set, $\frac{1}{2}$ and $\frac{1}{4}$ down sampling are shown in Figure 6.11. There is a trade-off between the accuracy of the registration and the speed of computation. This can be useful in surgeries where the deformation can be relatively high as in the case of open and minimally invasive surgery compared to a completely non-invasive surgery.

Figure 6.12 Comparison of registration errors using full, 1/2 and 1/4 point set

The performance of CPD algorithm was compared with the TPS-RPM algorithm [91, 92], which is considered to be a very similar algorithm but uses thin plate spline as the model for the underlying transformation. In the tests using the same image sets, both CPD and TPS-RPM gave comparable results. The average error for TPS-RPM was 1.9mm while that of CPD algorithm was 1.94mm. Figure 6.13 shows the error comparison between CPD and TPS-RPM algorithm (data table in APPENDIX A).

Figure 6.13 Comparison of error between CPD and TPS-RPM algorithm

Contrary to what [90] reported, TPS-RPM took less iterations (~86 iterations) compared to CPD (~149 iterations) to arrive at approximately the same accuracy. However, the average computation time for TPS-RPM was 24.12minutes which much greater than the computation time achieved by CPD algorithm (1minutes 12.7seconds) achieving the same level of accuracy (See Figure 6.14). The computation time for TPS-RPM algorithm is also not useful in the context of neurosurgical application as frequent monitoring and update is necessary (at least once in every 1-2minutes [10, 27]) for the accuracy delivery of treatment.

Figure 6.14 Comparison of Computation time between CPD and TPS-RPM

6.2 Hierarchical Hybrid Supervisory Controller

The constituent controllers of the hybrid controller are PID controller, Direct Model Reference Adaptive Controller and supervisory controller. In the following sections the author presents the simulation and experimental tests results of each constituent controller. The controllers

were tested on FUSBOT-NS end-effector. The experimental setup used for the testing of the controllers is also presented.

6.2.1 Experimental Setup

Figure 6.15 Schematic representation of the experimental setup for testing the hybrid control strategy

The hierarchical control strategy was tested on FUSBOT-NS with the help of Galil Motion Controller card [120]. The schematic of the experimental setup is shown in Figure 6.15.

Power supply: A 24V, 2A power supply was used for powering the amplifiers.

Driver: For each axis of the controller card, a power amplifier was used to convert the voltage output to current to drive the motors of the robot. The drivers used were brush-type PWM servo amplifier from Advanced Motion Control.

Computer: An Intel Pentium 4, 2 GHz computer was used for the implementation of the algorithms. The command signals for controlling the robot was given to the controller card from controller developed in this research so as to move the robot according to the inputs from the treatment plan updated by image registration unit. The inputs could also be directly given by the user.

Neurosurgical robot: The robot used for the controller testing is FUSBOT-NS end-effector developed by the Biomechatronics group, Robotics Research Centre, NTU. The mechanical structure of the robot and its modified design is described in Section 5.1 and 5.2. A needle of length 72.5mm was used to simulate the HIFU beam. The needle is fixed to the centre the HIFU transducer holder of FUSBOT-NS. The position of the tip of the needle will be position of the HIFU beam focus. Hence, measuring the position of the needle tip will give us the position of the HIFU beam focus. However, when the water chamber of the HIFU jig is filled with the HIFU coupling medium (degassed water), the opening of the jig is covered with a latex membrane. This membrane prevents the use of needle to act as the HIFU focus. In this case, bendable fixture was attached to the jig and the free end of the fixture was placed in such a way that the tip of the free end of the fixture acted as the HIFU focus. Schematic representations of these two arrangements are shown in Figure 6.16.

Figure 6.16 (a) Needle was used to simulate the HIFU beam, (b) A bendable fixture used to act as focus when coupling medium is filled in the water chamber of the HIFU jig

Controller card: Galil Motion Controller card DMC 1800 was used for this testing. It is a PCI 8-axis motion controller capable of controlling stepper and servo motor or a combination of both. The card has its own set of instruction opcodes dedicated for motion control. The Galil Win32

APIs were used for the purpose of implementation of the hybrid controller in this research [120, 121].

Stereovision camera: The end point position (needle tip) was measured with the help of a stereovision camera. The camera used was Point Grey Bumblebee®2 CCD camera [122]. Triclops Software Development Kit (SDK) and FlyCapture SDK were used for image acquisition and stereo vision processing.

A C++ program was written to convert the points in the stereo image to 3D co-ordinates (X,Y,Z) with respect to the camera co-ordinate frame. The underlying algorithm for the conversion stereo points to 3D co-ordinates is as follows:

- Using the images from the left and right camera of the Bumblebee®2 CCD camera, a 16 bit disparity map is extracted. The disparity map contains all the disparities of all points (distance between corresponding points in the left and right camera image) in the stereo image.
- Using the disparity information, the depth of each point w.r.t. the camera plane is calculated using, $depth = f.B/d$ where, f is the focal length (in pixels) of the camera, B is the baseline (in metres) i.e., the distance between the centres of projection of the two cameras (left and right) and d is the disparity (in pixels) of the point.
- After obtaining the depth which is Z in the camera co-ordinate frame, to determine X and Y , the projective camera equations, $X = r.Z/f$ and $Y = c.Z/f$ is used where, r and c are the pixel location in the 2D image, $r = row - row\ of\ Image\ centre$ and $c = column - column\ of\ Image\ centre$. This gives us the X,Y,Z of the desired point in the stereo image.

The author made use of the Application Programming Interfaces (APIs) provided by Point Grey for the purpose of implementing the code. The 3D co-ordinate obtained using the above algorithm was with respect to the camera co-ordinate axes. In order to obtain the point (X,Y,Z) with respect to the target co-ordinate a simple frame-to-frame transformation was performed. A schematic diagram of the setup using stereo vision camera and its co-ordinate frames are shown in Figure 6.17.

Figure 6.17 Schematic representation of stereo-camera, FUSBOT-NS end-effector and its co-ordinate frames

6.2.2 SimMechanics Model of FUSBOT-NS end-effector

The end-effector structure is simulated using the MATLAB Simulink software. Model of the end-effector parallel structure was built using MATLAB SimMechanics Toolbox based on the model derived in Section 5.3. The SimMechanics block diagram of the plant (manipulator) is shown in Figure 6.18. The manipulator link construction is shown in Figure 6.19. The property of the model, mass, centre of gravity and inertia tensor, was entered based on Pro/E model of the end-effector. The joint is actuated by a Joint Actuator module from the SimMechanics library. The torque to the Joint Actuator is received from the PID controller block of the system. The outputs of the joints are sensed using the Joint Sensor module and fed back to the PID controller block.

The Reference Trajectory block (Figure 6.20) deals with the inverse kinematics of the end-effector. For the desired trajectory, the block finds the required input to be given to the joint actuators. It performs these calculations based on the equations (5.1) and (5.3) given in Chapter 5. An example of the trajectory would be rotation of the jig about the X and Y axis (pitch and yaw) for an angle $\pm 10^\circ$ or in-out motion of the transducer holder along the Z-axis for a distance of $\pm 5\text{mm}$. The end-effector must move in a way so as to target each and every point in the entire volume of the tumour. In the simulation, the input to the reference trajectory block is

the pitch angle, yaw angle and the linear translation required for the end-effector to reach a particular target lesion.

Figure 6.18 SimMechanics model of the FUSBOT-NS end-effector

Figure 6.19 SimMechanics model of the parallel link of the end-effector

Figure 6.20 Reference trajectory block

6.2.3 Simulation of FUSBOT-NS using PID controller

The PID controller model developed using Simulink is shown in Figure 6.21. The reference trajectory from the Reference Trajectory block and the position feedback from the Plant block (discussed in the previous subsection) are the input to this controller block. The output of the block is torque required by the actuators to follow the desired trajectory. Here the torque is proportional to the error signal.

$$T = K_p e(t) + K_i \int e(t) + K_D \frac{de(t)}{dt}, \quad e(t) = d_r(t) - d_i(t) \quad (6.1)$$

where, $d_r(t)$ is the reference trajectory input to the i^{th} linear actuator and $d_i(t)$ is the feedback signal from the i^{th} linear actuator. K_p , K_i , K_D are the PID gains. The overall system block diagram, consisting of the Reference trajectory block, PID Controller and the FUSBOT-NS end-effector model is shown in Figure 6.22.

Figure 6.21 PID controller Simulink model

Figure 6.22 Overall system block diagram

PID controller performed well in structured scenario where there are no fast variations or disturbances. This can be observed in Figure 6.23, where a square wave of amplitude

0.1745units and frequency 0.01Hz was used as the reference signal. Here the end-effector is rotated (pitch motion) by an angle 10 degrees (0.1745 rad). Figure 6.23 shows the response in Link 1 and Link 2 (E axis and H axis respectively).

Figure 6.23 Response at the actuated joint at link1 and link 2 using PID control to a square of amplitude 0.1745units and frequency 0.01Hz

However, operation theatre environment is very unstructured and noisy. Hence it is important that the controller is able ensure robust performance such conditions. However, as can be seen in Figure 6.24, the performance of the PID controller was poor and the system became unstable in the presence of random high frequency noise. In Figure 6.24, we see the response of the actuated joints of link 1 and link 2 to the same square wave but with random noise of amplitude upto 0.1 units and frequency 10Hz. A similar simulation test performed using the direct model reference adaptive controller gave very good results. The simulation of the system using DMRAC controller and results are discussed in Section 6.2.5.

Figure 6.24 Response at the actuated joints at link 1 and link 2 using PID control to a square of amplitude 0.1745units and frequency 0.01Hz+random noise of amplitude up to 0.1units and frequency 10Hz

6.2.4 Experimental Testing using PID controller

Since, the FUSBOT-NS end-effector has a parallel structure, all the links had only up-down motion. The motion of each motor was tested using Galil controller and its associated development kit [120]. The distance range (0-18mm) was decided according to the workspace of FUSBOT-NS discussed in Section 5.3.2, which was derived based on human anthropomorphic data and location of brain tumours. The speed and direction of the motion was varied using Galil controller by giving the desired speed encoder counts (100000cts (2mm/second), 250000cts (5mm/second), 300000cts (8mm/second)). The distance travelled by each link (thus the error as well) was measured using a vernier caliper. The errors of each link were calculated with respect to their respective co-ordinate frames. E,F,G,H represents the four axes of the FUSBOT-NS end-effector.

Table 6.2 Test parameters for the four axes of FUSBOT-NS

Axis	Speeds	Range of Distances	Direction
E	2, 5, 8mm/s	0-18mm	Up-down
F	2, 5, 8mm/s	0-18mm	Up-down
G	2, 5, 8mm/s	0-18mm	Up-down
H	2, 5, 8mm/s	0-18mm	Up-down

The errors were plotted based on the measurement data collected during the testing of the end-effector PID control.

The controller was implemented using the in-built function of the Galil Software Development kit (SDK) for PID controllers. The gains obtained during the tuning of the PID controller were stored in the Galil controller. A C++ program was developed in Microsoft Visual C++ platform for the implementation of the PID controller. With the help of the C++ program, the interface between the controller and the FUSBOT-NS motors was achieved. The reference encoder counts and the current motor position counts could be read in real-time with the help of Galil DMC32 APIs.

Figure 6.25 Error graph of E axis: The link was moved within a distance range of 0-18mm in both up and down directions at three different speeds

We can easily observe in the Figure 6.25 to Figure 6.28 that the errors are all well within the acceptable error limit of 0.2mm except for distances equal to or more than 12mm and speed above 5mm/second. These errors may have been caused due to increased dynamic effects such as friction on the lead screws during fast motion over longer distances.

Figure 6.26 Error graph of F axis: The link was moved within a distance range of 0-18mm in both up and down directions at three different speeds

Figure 6.27 Error graph of G axis: The link was moved within a distance range of 0-18mm in both up and down directions at three different speeds

Figure 6.28 Error graph of H axis: The link was moved within a distance range of 0-18mm in both up and down directions at three different speeds

6.2.5 Simulation of FUSBOT-NS using DMRAC

Using MATLAB SimMechanics, simulation of the controller was performed. The controller model was built using the software and used to control the FUSBOT-NS end-effector. The end-effector structure model described in Section 6.2.2 was used for testing DMRAC. The SimMechanics model of the overall system with the DMRAC controller is shown in Figure 6.29.

DMRAC was modelled based on the equations 4.2-4.26. The SimMechanics model is shown in Figure 6.30.

Figure 6.29 SimMechanics model of the overall system with DMRAC

Figure 6.30 SimMechanics model of the DMRAC simulated

Here, the reference command u_m was given as a square wave of amplitude 0.1745 units and frequency of 0.01Hz. Here the end-effector is rotated (pitch motion) by an angle 10 degrees (0.1745 rad). In Figure 6.31, we see that the controller follows the transition well and also

settles at the steady value quickly. The overshoot observed in the simulation is because the controller is tuned for high adaptation rate. However, it must be highlighted that in the experimental testing no overshoot was observed. This is due to the approximation made in the mechanical model of the end-effector used for simulation.

Figure 6.31 Response (DMRAC) at the actuated joint of link1 and link 2 to the square wave of amplitude 0.1745 units and frequency 0.01Hz

Next, the reference command but with random noise of frequency up to 10Hz and amplitude 0.1units was given to the system to see the robustness of the controller. In Figure 6.32, we see that the DMRAC continues to perform well even in the presence of high frequency noise unlike in the case of PID controller which made the system unstable (Figure 6.24).

Figure 6.32 Response(DMRAC) at the actuated joint of link 1 and link 2 to the square wave of amplitude 0.1745 units and frequency 0.01Hz+random noise of amplitude up to 0.1units and frequency 10Hz

6.2.6 Experimental Testing using DMRAC

DMRAC was implemented and tested using the Galil Motion Control card and software. The controller was tested using the same testing method used for testing the PID controller. The error was measured for various distances ranging from 0 to 18mm, for three different speed counts (100000, 250000 and 300000 counts) and for both directions (up and down). The distances travelled by each axis were measured using a vernier calliper. Figure 6.33-Figure 6.36 shows the graph of the error measurements.

It can be seen quite clearly that the DMRAC was successful in keeping the error below the tolerable limit of 0.2mm for the entire range of motion except for a few points. Only 5 out of 99 measurements had an error above the limit. This can be attributed to human error during measurement or sudden variation in the power supply during measurement and hence can be considered as outliers. In the case of PID controller, the controller failed to keep the error

below 0.2mm for distances above 12mm at higher speeds. DMRAC showed a 21% better accuracy compared to PID controller in this range of motion. However, PID controller showed slightly better accuracy (1%) for distances below 12mm at lower speeds (at 2mm/second and 5mm/second). In the hybrid controller, since it can choose between any of the two controllers during operation, the performance of the overall system will be in acceptable limit for all range of distances and speeds. The simulation and experimental testing of the hybrid controller is presented in the following section.

Figure 6.33 Error graph of E axis for DMRAC: The link was moved within a distance range of 0-18mm in both up and down directions at three different speeds

Figure 6.34 Error graph of F axis for DMRAC: The link was moved within a distance range of 0-18mm in both up and down directions at three different speeds

Figure 6.35 Error graph of G axis for DMRAC: The link was moved within a distance range of 0-18mm in both up and down directions at three different speeds

Figure 6.36 Error graph of H axis for DMRAC: The link was moved within a distance range of 0-18mm in both up and down directions at three different speeds

6.2.7 Simulation of FUSBOT-NS using Hybrid Supervisory Controller

The formulation of the hybrid supervisory controller was presented in the Chapter 4, Section 4.2.3. The plant events recognized by the controller were explained along with the formulation. An estimator-based supervisory control was proposed by the author. Based on the estimated performance of the PID and DMRAC controllers in the hybrid structure, the supervisor chooses the appropriate controller for optimum accuracy. In this section, the simulation and the experimental testing of the controller are presented.

A Simulink model of the proposed hierarchical hybrid controller was built using the Simulink software. Figure 6.37 shows the Simulink model. The PLANT includes the two constituent controllers (PID and DMRAC) of the hybrid controller and also the neurosurgical robot (FUSBOT-NS). The SUPERVISOR carries out all the decision making process based on the plant events described above. On the left side of the block diagram we see the imaging system, Emergency shutdown unit and the human operator. The imaging system, gives the trajectory input from

the treatment plan updated by the intra-operative imaging. The human operator block gives the input from the user in the event of a failure of the imaging system or human intervention.

For testing purpose, three switches are provided so as to simulate the event of 1) imaging system failure, 2) emergency shutdown and 3) intervention by the human operator/surgeon. Based on these inputs, as discussed in Section 4.2.3, the interface generates appropriate signals and based on the interface signals, the supervisor block takes decision and controls the system accordingly so as to ensure a safe and accurate operation or fail in a very controlled manner. In this work, however, the fail-safe operation of the robot is not focused upon. The accuracy of the robot positioning is main criterion. In the simulation, in the event of a failure (generated by switching on and off the appropriate switches in the model), the operation of the robot is brought to a halt.

Figure 6.37 Simulink model of the hierarchical hybrid controller

The stability of the system in the event of switching between the constituent controllers in the hybrid controller was considered during the simulation as well as testing of the system. The switching between the PID and DMRAC controllers were tested in the simulation in the event of the initialization ($\neg \tilde{x}_1$), gross positioning of the end-effector by the base manipulator ($\neg \tilde{x}_2$)

during the surgery and also event of change back to surgery ($\widetilde{x}_2$). The response of Link 3 to these events is shown in Figure 6.38. We can see that switching between the controllers were successful without causing any instability to the system. However, the system takes some time to settle when there is a switch from PID to DMRAC, which is quite evident from the excessive oscillation in the response at the point where the switching occurs. This oscillations, however, was settled without leading to the overall instability of the system. One of the ways to ensure a smooth transition is to make the switching when the system is in a steady state.

Figure 6.38 Response of Link 3 to switching between PID and DMRAC in the event of initialization, gross positioning and back to surgery; The controller select signal is also shown in the figure

6.2.8 Experimental Testing and Comparison-Hybrid Supervisory Controller

The same test parameters used for PID and DMRAC, as shown in Table 6.2, was used for the hybrid controller testing as well. However, the controller was tested for only two speeds (2mm/second and 8mm/second) as the performance of the constituent controllers (PID and DMRAC) showed marked difference only at 8mm/second.

Since the Hybrid controller was already built in Simulink for simulation, this model was used for the implementation of the controller. The controller was interfaced to the Galil controller card with the help of Galil controller which support direct access to Windows Dynamic Link Libraries. It is possible to use the DMCWin 32 API through MATLAB using this feature [121]. Figure 6.39 to Figure 6.42 shows the error graphs on each axis of the end-effector during the testing of the hybrid controller and Figure 6.43 and Figure 6.44 shows the combined error of all axes at speeds 2mm/second and 8mm/second. The PID and the DMRAC results are also shown in the combined error graph for comparison of the performances.

Figure 6.39 Error graph of axis E during experimental testing of hybrid controller

Figure 6.40 Error graph of axis F during experimental testing of hybrid controller

Figure 6.41 Error graph of axis G during experimental testing of hybrid controller

Figure 6.42 Error graph of axis H during experimental testing of hybrid controller

Figure 6.43 Comparison of error performance between PID, DMRAC and Hybrid controller- Combined error of all axis at speed 2mm/second and distance below and above 12mm

Figure 6.44 Comparison of error performance between PID, DMRAC and Hybrid controller- Combined error of all axis at speed 8mm/second and distances below and above 12mm

From the graphs we can clearly see that hybrid controller is able to take the best out of the two constituent controllers. The overall accuracy is well within the error tolerance of 0.2mm. Both PID and DMRAC have shown good and comparable performances at low speed and shorter distances. However, the accuracy of PID controller deteriorates at higher speeds and when the distance moved is more than 12mm. This may be due to its inability to adapt to the dynamic effects such as friction, which are more pronounced at high speeds. Low speed motion would be primarily used for the homing position of the robot at the start of the surgery, during the initial and intermediate gross positioning of the end-effector close to the patient's head. The hybrid supervisory controller was able to switch between the two controllers depending on the estimated performances during the operation of the robot and thereby improve the overall accuracy of the robotic system compared to just using a PID controller. The statistical measures from the tests conducted are presented in Table 6.3. A 95% confidence interval of mean was also constructed.

Table 6.3 Statistical measures from the error analysis of hybrid controller testing

Statistical measures	SPEED 2mm/s					
	PID		DMRAC		Hybrid	
	Inner (<=12mm)	Outer(>12mm)	Inner (<=12mm)	Outer(>12mm)	Inner (<=12mm)	Outer(>12mm)
Mean	0.0832	0.2019	0.0827	0.1656	0.0835	0.1671
Standard Deviation	0.0614	0.0345	0.0496	0.0473	0.0492	0.0463
Maximum	0.28	0.29	0.21	0.27	0.21	0.28
Confidence Interval of Mean (95%)	±0.013	±0.008	±0.011	±0.011	±0.011	±0.011

Statistical measures	SPEED 8mm/s					
	PID		DMRAC		Hybrid	
	Inner (<=12mm)	Outer(>12mm)	Inner (<=12mm)	Outer(>12mm)	Inner (<=12mm)	Outer(>12mm)
Mean	0.0842	0.2341	0.0885	0.1794	0.087	0.1798
Standard Deviation	0.0644	0.0502	0.0569	0.0492	0.0559	0.0457
Maximum	0.3	0.34	0.25	0.28	0.23	0.27
Confidence Interval of Mean (95%)	±0.012	±0.012	±0.01	±0.012	±0.01	±0.011

6.2.9 Experimental testing based on End point Measurement

As discussed in Section 4.1, three treatment protocols are considered in HIFU-based neurosurgery- Adjacent points, Distant Points and Arbitrary point protocol. The robot movement characteristics expected in each of the treatment protocol is shown in Table 6.4.

In the Adjacent Point protocol, neighbouring treatment points in the tumour are targeted in a pre-planned sequence. Hence, the distance moved from one point to the other is small but, because of the high temperature at the neighbouring point, a cooling down time needs to be allowed before targeting the next point (adjacent to the already targeted point). Hence, the movement speed requirement is low. From our testing, we can see that PID gives good accuracy performances at lower speed and shorter distances.

In the Distant Point protocol, there is no waiting period for cooling down of the targeted tissue as the point chosen to be targeted is far from the previous targeted point. Hence, the distance

to be moved is longer, the speed of motion has to be faster and movement sequence is pre-defined. Based on the test results we can see that DMRAC can give the acceptable accuracy performance for the movement characteristics described.

In the Arbitrary Point protocol, the surgeon specifies which point needs to be targeted. This protocol is generally followed in the event where a human supervision is necessary like in the case where a critical brain structure is close to the intended treatment points. In this protocol, the points are chosen based on the surgeon's judgement. There is no fixed sequence for the treatment points. Hence, the distance moved and the expected speed of motion is also unpredictable. Either of the controllers can give good performance depending upon the current state of the robotic system. The hybrid controller chooses the controller which can give the best accuracy at the given point of time.

Table 6.4 Three HIFU treatment protocols and expected movement characteristics

TREATMENT PROTOCOL	CHARACTERISTICS		
	Speed	Distance	Movement Pattern
Adjacent Point	Slow	Short	Pre-defined
Distant Point	Fast	Long	Pre-defined
Arbitrary	Slow	Varies	Unstructured

PID controller, DMRAC and the developed hybrid controller were tested based on the end point measurement using the stereo vision camera. 3D co-ordinates of the end-effector end point were obtained with the help of the algorithm discussed in the Section 6.2.1. The controllers were tested for the Adjacent point protocol and Distant Point protocol.

For the testing of the accuracy of the robot positioning, a series of target points were selected. After the robot moved to each of the selected point, the position of the needle tip were compared with the intended point and the error was computed. A Graphical User Interface (GUI) was created, using MATLAB software, for the purpose of selecting the target points to which the robot has to be move the needle tip. The GUI depicts the tumour as a sphere of specified radius in the target co-ordinate frame. With the help of a slider and mouse pointer,

the user can choose different slices within the tumour and choose the target points (See Figure 6.45).

Figure 6.45 Graphical User Interface for selecting treatment point on a tumour

For the test, 40 points were selected as the target points for both the Adjacent Point protocol and Distant Point protocol (Section 4.1). After the robot moves the needle tip to the each target point, the position of the needle tip is obtained with the help of the stereovision camera system and compared with the desired position.

Adjacent Point protocol

The inner and outer regions of the robot workspace is defined as the workspace region within a radius of 8mm (≤ 6 degrees pitch or yaw angle) and region beyond 8mm radius (> 6 degrees pitch or yaw angle). Due to presence of HIFU coupling medium in the FUSBOT-NS end-effector, during pitch/yaw motion, there is a variation in the mass distribution of the end-effector. However, in the Adjacent Point protocol the next target point is not more than 1mm away from the current target point. Hence the variation during the transition is not significant. Also, since the distance moved is less, the error due to lead screw friction is also less. The effect of non-linearities such as variation in moment of inertia and friction are not significant in this protocol. Hence, the performance of PID controller and DMRAC are comparable. The comparison of accuracy of the robot using PID controller, DMRAC and the hybrid controller for the Adjacent Point protocol are shown in the Figure 6.46.

Figure 6.46 Accuracy comparison between PID controller, DMRAC and hybrid controller for Adjacent Point protocol

Table 6.5 Statistical measures from the error analysis of hybrid controller testing for Adjacent Point protocol

Statistical measures	Adjacent Point protocol					
	PID		DMRAC		Hybrid	
	Inner (<8mm)	Outer(>8mm)	Inner (<8mm)	Outer(>8mm)	Inner (<8mm)	Outer(>8mm)
Mean	0.0803	0.121	0.0847	0.11	0.0813	0.109
Standard Deviation	0.028	0.033	0.029	0.026	0.030	0.027
Maximum	0.12	0.15	0.12	0.14	0.13	0.13
Confidence Interval of Mean (95%)	±0.01	±0.02	±0.01	±0.02	±0.01	±0.02

Distant Point protocol

On the other hand, the case of Distant Point protocol, as the name suggests, the distance between subsequent target points are big. For example, after targeting a point on the tumour, the next point would be diametrically opposite point on the tumour. This can lead to bigger change in the moment of inertia compared to the case in Adjacent Point protocol and also since the distance to be moved is big, the effect of friction is also high. This leads to more errors when using only PID controller. We can see from the accuracy measurements (See Figure 6.47) that PID controller performs poorly when the points targeted are in the outer

region of the workspace while DMRAC performs well in the same region. DMRAC showed a 22% better accuracy compared to PID controller in the outer regions of the workspace. The performance of PID controller and DMRAC are quite similar in the inner regions of the workspace. The supervisor in the hybrid controller finds the best performing candidate controller and switches to it so as to ensure acceptable performance.

Figure 6.47 Accuracy Comparison between PID controller, DMRAC and hybrid control in Distant Point protocol

Table 6.6 Statistical measures from the error analysis of hybrid controller testing for Distant Point protocol

Statistical measures	Distant Point protocol					
	PID		DMRAC		Hybrid	
	Inner (<8mm)	Outer(>8mm)	Inner (<8mm)	Outer(>8mm)	Inner (<8mm)	Outer(>8mm)
Mean	0.131	0.238	0.139	0.185	0.133	0.188
Standard Deviation	0.036	0.034	0.035	0.025	0.039	0.022
Maximum	0.21	0.3	0.3	0.23	0.22	0.24
Confidence Interval of Mean (95%)	±0.01	±0.02	±0.01	±0.01	±0.01	±0.01

Since the implementation of hybrid controller and the communication between the controller and the Galil controller card were performed in MATLAB, there was no noticeable delay in the interface of the controller and controller card. However, the hybrid controller showed more computation time compared to PID and DMRAC due to the increased computation

requirement. Delay was observed at some controller switching instances. Computation time problem can be alleviated by using parallel computing techniques and also using more powerful computers. By using better memory allocation techniques, the computation time was reduced.

Stability of the overall robotic system is a critical factor in the functioning of the system. The stability of the system was observed at the time of switching between PID to DMRAC or vice versa. The overall stability of the robot was maintained at every switching instance. This may be due to the simplicity of the system as very few plant events recognized by the supervisory controller during normal operation. However, noise or vibration was observed at axis F during switching from PID to DMRAC. But the vibration settled very quickly (within 3-4seconds) and reached the desired position. This may be due to error in the tuning of the controllers. The noise was reduced by re-tuning the controllers but the author was not possible to eliminate the noise completely.

6.3 Validation of Proposed Control Strategy for Neurosurgical Robots

The three most important components in a neurosurgical robotic system i.e., the neurosurgical robot, real-time deformation tracker and controller were devised and tested in this work. In Figure 6.48, the schematic diagram of the complete neurosurgical robotic system with the dynamic deformation tracker, hybrid supervisory controller and FUSBOT-NS end-effector is shown. In this section, the working of the complete system is presented and proposed system is validated.

At the start of the surgical procedure, the robot controller parameters are initialized and the robot is brought to a pre-defined home position. Based on the pre-operative treatment plan, the end-effector of the robot, which carries the surgical tool, is moved to a point close to the patient's head (gross positioning). The treatment points specified in the treatment plan are then targeted so as to ablate the entire tumour. The treatment points are updated based on the updated tumour position from the dynamic tracker unit. During the course of the surgery, the end-effector positioning with respect to the patient's head may need to be re-positioned.

Figure 6.48 Schematic representation of the proposed system for non-invasive robotic neurosurgery

The same setup used for the testing of the hybrid supervisory controller and the deformation estimation strategy was used for the validation of the control strategy (See Figure 6.2 and Figure). A set of points were initially selected as the treatment points and the co-ordinates of the points were stored in text file from which the robot read the target co-ordinates and oriented the end-effector accordingly.

A linear motion was given to the target phantom by the motorized jig, in the direction of gravity at varied speeds of 0.524mm/second, 0.393mm/second and 0.262mm/second for a distance of 40mm. This was used as it was seen in the literature study that the major component of the brain deformation was in the direction of gravity. However, the deformation of the brain tissue is much slower than the speeds selected for the phantom motion. For the validation experimental, ultrasound imaging system was used to obtain the intra-operative US images and the location of the tumour was tracked by the dynamic deformation tracker and the updated treatment position was fed up back to the robot.

The focus of the HIFU beam was simulated with the help of a needle of 72mm length which was attached to the end-effector of FUSBOT-NS. The tip of the needle was considered as the common focal point of the HIFU beams. The position of the tip of the needle attached to the end-effector was monitored by a camera in order ascertain the robot tracking of the dislocation

given to the phantom. The images captured by the camera was later analysed to verify whether the robot was able to accurately track the dislocation given to the brain phantom.

Figure 6.49 Tracking of the brain phantom deformation by the robot end-effector in the proposed surgical protocol

From the graph presented in Figure 6.49, we can see that the robot was able to track the displacement given to the phantom with the help of the dynamic deformation tracker proposed and implemented in this research project. The figure shows the end-effector tip position with respect to the phantom position using the deformation tracker. The tip of the needle attached to the end-effector, which simulates the HIFU beam focus, was tracked with the help of Bumblebee 2 stereo CCD camera and the Triclops stereo vision system. The position of the phantom was tracked using the Dynamic Deformation tracker and the end-effector was adjusted according to the target position input from it.

Error between Movement given to the phantom and Position output from the Deformation Tracker

Maximum error=1.11mm

Mean error=0.362mm

Standard deviation=0.26mm

Figure 6.50 Error between the Deformation tracker output and movement given to phantom

Error between the input from Deformation tracker and the position of the tip of the needle (HIFU beam focus)

In the analysis of the images captured of the tip of the needle, which acted as the focal point for the HIFU beam, it was observed that there was a lag of 0.62seconds in the tracking of the phantom. This lag can be attributed to the time taken to move the end-effector from point to the next and also the computation time for the tumour tracking. Since a speed of 0.262mm/second to 0.524mm/second was given for the brain phantom motion, the amount of motion missed in this time frame is quite large compared to the real scenario where a displacement of 50mm was observed at the end of tumour resection procedure, which generally takes about 6-7 hours. This can be considered the worst case scenario as the amount of displacement is much less in the case of minimally invasive or non-invasive procedures. The error graph is present in Figure 6.51.

Maximum error observed=1.9mm

Mean error=0.267mm

Standard deviation=0.243m

Time lag between end-effector position and deformation tracker output=0.62seconds

Figure 6.51 Error between the output of Deformation tracker and the end point position

6.4 Summary

This chapter presents the implementation of the dynamic deformation tracker proposed and formulated in Chapter 3 and the hybrid supervisory controller formulated in Chapter 4. The proposed deformation tracker is a two stage tracker where a gross position estimation of the target is performed with help of template matching algorithm and in the second stage, finer deformation estimation is performed using Coherent Point Drift algorithm. The two algorithms were tested for both accuracy and computation time. Template matching algorithm achieved an accuracy of 0.4mm and a computation time of 0.8seconds. This provides the approximate deformation estimation in a very short time which is greatly beneficial in real-time tracking of intra-operative brain shift. CPD algorithm, which is a non-rigid point-based image registration algorithm, also gave very encouraging results. The average error was 1.94mm with a computation time of 1minute 17.2seconds. This is well within the desired accuracy and computational time range where the accuracy of a surgeon performing surgery is in the range of 3 to 5mm and the desirable deformation estimation time is every 1 to 2minutes. The performance of CPD was compared with its closest (in terms of performance) algorithm which is the Thin Plate Spline Robust Point Matching algorithm. The accuracy of both was found to be comparable (1.9mm for TPS-RPM). However, in terms of computation time TPS-RPM performed poorly (average time of 24.12minutes). The accuracy of CPD was found to have strong positive

correlation to the initial error (amount of deformation). CPD was found to be performing well even in the presence of noise and also in the absence of the full feature in the images. The computation time performance was drastically reduced by a factor of 5 to 9 by applying a down-sampling factor of $\frac{1}{2}$ and $\frac{1}{4}$ to the number of points in the image point sets. However, when applying the down-sampling factor there is trade-off between computation time and accuracy. The accuracy for $\frac{1}{2}$ and $\frac{1}{4}$ down-sampling factor was 2.18mm and 2.25mm.

The hybrid controller proposed in Chapter 4 was also implemented and tested on FUSBOT-NS end-effector. The controller was developed using the C++ program and MATLAB/Simulink programming. Galil controller card was used as an interface between the developed controller and the robot motors. The robot positioning accuracy using PID controller, DMRAC and the proposed hybrid supervisory controller in the Distant Point protocol and Adjacent Point protocol was tested. A stereo vision camera, Bumblebee 2, was used for measuring the end point accuracy.

In the Distant Point protocol, DMRAC showed a 22% better accuracy compared to PID controller in the outer regions of the workspace (radius $>8\text{mm}$) and almost same accuracy in the inner regions of the robot workspace. The poor performance of PID can be attributed to the greater movement by the lead screw and hence greater friction when moving to the outer part of the workspace. Also due to the presence of the coupling medium in the HIFU jig, as the rotational motion becomes greater, the change in moment of inertia is also greater. DMRAC is able to handle these dynamic changes much better.

In the Adjacent Point protocol, both PID controller and DMRAC performed equally. This may be due to the fact that in this protocol, the subsequent target points are adjacent to each other, less than or equal to 1mm apart. Hence, the amount of movement required and the amount of change in the HIFU jig mass distribution are very minimal. Since PID controller is considered the default controller, in the event where both controllers are performing equally well, the PID controller is chosen as the controller in the feedback loop.

The proposed deformation tracker and hybrid controller were integrated and tested. The robotic system was tested by tracking a dynamically moving target. The target was moved in

the direction of gravity at three different speeds-0.524mm/second, 0.393mm/second and 0.262mm/second. The developed system was able to successfully track the target with a mean error of 0.267mm and a maximum error of 1.9mm. There was time lag of 0.62seconds. This is due to the computation time of the deformation tracker as well as the controller. The speeds used for the moving target is much greater than the actual speed of the deforming target in a neurosurgery and hence this test condition can be considered as a worst scenario.

CHAPTER 7. CONCLUSION AND FUTURE WORK

The main objective of this research project was to develop and analyse a control strategy for image-guided non-invasive neurosurgical robots which takes into account the intra-operative brain tissue deformation. There are mainly two aspects to this strategy- 1) tracking the dynamic deformation and updating the treatment plan and 2) control of the neurosurgical robot to accurately target the treatment points as per the updated treatment plan. A two-stage approach which dynamically tracks the rigid as well as the non-rigid component of the brain shift using a computationally fast template matching algorithm and a point-based non-rigid image registration algorithm (coherent point drift) was proposed and implemented for the image control. For the robotic control, a hybrid supervisory control with PID and Direct Model Reference Adaptive control as its constituent controller and an estimator-based supervisor was proposed and implemented. The proposed control strategy was tested and validated on a representative neurosurgical robot, FUSBOT-NS which was developed by Biomechatronics group in Robotics Research Centre, NTU.

7.1 Conclusion

The anatomy of the target organ, which is the brain, the most common brain abnormality, brain tumours and the nature and extent of the phenomenon of brain shift were studied in order to understand the key problems faced in neurosurgery. Some of the important points understood in this study are:

- 60% of all brain tumours are superficial tumours i.e., they occur at the surface of the brain, within 20mm from the dura mater[35].
- Brain, being a soft tissue organ, deforms continuously and unpredictably during surgical procedures. Hence, treatment time for surgery becomes a critical factor for accuracy of treatment delivery.
- A maximum displacement of 50mm has been observed at the end of neurosurgery (6-7 hours) in the brain in studies [10] conducted using intra-operative imaging. This can be considered as a worst case scenario as the extent of deformation would be much less in the case of non-invasive surgery.

- Deformation has been observed in the brain not only after the opening of the skull but also prior to opening of the dura mater [7, 8, 10, 77].
- The major component of the brain deformation is in the direction of gravity. The most commonly observed deformation is the sinking of the brain tissues [7, 8, 10, 77].
- The causes for brain deformation are not known fully. Some of the identified causes are leakage of cerebro-spinal fluid, use of diuretics and anaesthetics, loss of intra-cranial pressure, the position of the patient's head during surgery [7, 9, 10, 77].

Stereotactic Radiosurgery treatment was studied in more details so as to gain an understanding of the principles of both frame-based and frameless surgery. Similarly, a non-invasive modality High Intensity Focused Ultrasound (HIFU), which has shown encouraging results in recent years, was also investigated. The roles of robotics in medicine, especially neurosurgery, were studied so as to understand the range of tasks that robots are capable of performing in the surgical environment. Various image registration algorithms were explored and understood as image registration algorithms plays a major part in the development of the control strategy proposed in this research work.

Dynamic Deformation Tracking

The dynamic deformation tracker is a crucial component in the proposed non-invasive neurosurgical robotic system. This unit is the eye of the robot and also the surgeon as the brain tumour(s) are not directly accessed as in the case of open surgeries. Hence, the accuracy of the brain tumour position estimation and also the speed at which the imaging unit is able to track the tumour is of prime importance. Based on the tissue deformation estimation, the treatment plan developed pre-operatively is updated during the surgical operation.

The strategy for the estimation of tissue deformation is based on two criteria:

1. The ability to accurately track the dislocation and non-rigid deformation. The accuracy achieved by clinicians without imaging is in the range of 3-5mm [27]. Required accuracy for imaging should be within 2mm so that the overall accuracy (tracking errors+ robot motion errors) would be well within this range.

2. Fast image acquisition and computation time. It is required to estimate brain shift as frequently as possible (at least once in every 1-2minutes) [10, 27].

Two methods were considered for this task, one is the development of a biomechanical model of the brain tissue deformation and the other is the use of intra-operative imaging. The former was rejected as the phenomenon of brain shift is not predictable and there are many factors which influence its pattern. Modelling such a phenomenon would be computationally taxing and also probably lead to gross errors. Intra-operative imaging method was used in this work as it is much more reliable compared to biomechanical models [10]. Also, with the advancement of imaging technology like ultrasound imaging, it is possible to monitor the brain deformation in real-time without interrupting the course of the surgery [22, 23].

In this work, a two-stage dynamic brain deformation estimation strategy was proposed, implemented and tested. Ultrasound imaging was used for the intra-operative imaging. The proposed tracking strategy was tested using brain phantoms in the experimental setup described in Section 6.1.1. Brain phantoms were made using commercially available agar agar and the displacement of the phantom was simulated by moving the phantom using a motorized jig. The deformation and dislocation is estimated in two stages- 1) a coarse estimation of the tumour dislocation is performed with help of a fast and computationally light template matching algorithm. The test trials show that the dislocation estimation was possible in average time of 0.8seconds time with an average error of just 0.4mm, 2) a fine estimation of the brain tissue deformation was performed with help of a CPD algorithm, which is a point-based non-rigid image registration algorithm. This algorithm could estimate the deformation within an average error of 1.94mm in average computation time of 72.7seconds. The performance of CPD was compared to its closest performing algorithm Thin Plate Spline-Robust Point Matching algorithm (TPS-RPM). The accuracy of both was found to comparable. However, the computation time for TPS-RPM was very high (24.12minutes) compared to CPD. By introducing a down-sampling factor ($\frac{1}{2}$ or $\frac{1}{4}$) the computation time for CPD was reduced by a factor of 5 to 9. However, the registration accuracy reduced to 2.18mm and 2.25mm for $\frac{1}{2}$ and $\frac{1}{4}$ down-sampling factors respectively. This can be useful in the case where there is fast deformation and

hence requires faster deformation estimation updating. The tracking algorithm used in this work exploited the temporal continuity of deformation. The proposed strategy utilises the transformation estimated till the previous estimation $T_{US}(n-1)$ and composes it with the deformation estimated between the US_{n-1} and US_n , $dT_{US}(n)$ for the tracking of brain shift. Using this tracking strategy, we limit the amount of deformation to be estimated between two images and hence reduce the registration error and also the computation time.

Hybrid Supervisory Controller

In this research, a hierarchical hybrid supervisory control, which combines PID controller, model reference adaptive controller and a supervisory control, was proposed. A three-layer hierarchical control architecture is proposed and implemented in this work. The first layer, which is the high-level supervisor level, is the decision making layer. It receives inputs from various sources such as the dynamic deformation tracking unit, treatment plan, robot sensors and the human operator or surgeon. Based on these inputs it receives during the course of the surgery, it makes decisions and communicates to the lower layers for the smooth and accurate operation of the neurosurgical robot. High-level supervisor is the layer which also decides which of the two constituent controllers in the hybrid controller controls the robot based on the estimated performance of each controller. The mid-level layer acts as an interface between the high-level supervisor and low-level control layer. It is also the layer which switches between PID controller and DMRAC as decided by the Supervisor. The low-level control layer deals with the accurate control of the neurosurgical robot. In this layer the selected controller is in loop with robot via its sensors.

The control architecture was experimentally tested on FUSBOT-NS. FUSBOT-NS is a HIFU-based neurosurgical robot. The end-effector of FUSBOT-NS is a parallel robot with three degrees of freedom- pitch, yaw and translation motion. The parallel links of the robot is driven by a lead screw mechanism using a DC servo motor. The inverse kinematics and dynamics modelling of the end-effector of FUSBOT-NS was formulated. The kinematics is deduced using the geometric method while the inverse dynamics was obtained using the principle of virtual work.

Simulation and experimental tests were conducted for each of the constituent controllers in the hybrid controller. Simulation results showed that PID controller performed well in slow and predictable circumstances but failed to give satisfactory performances in noisy and fast changing environment. However, the direct model reference adaptive controller showed robustness in the simulation results even in the presence of noise. The experimental testing confirms the simulation results. The controllers were tested for motions over different directions, range of speeds (2mm/second, 5mm/second, 8mm/second) and range of distances (0-18mm). The error analysis of PID controller and DMRAC showed that DMRAC had 21% better accuracy for longer distances (outer regions of workspace) at higher speeds (above 8mm/second). However for short distances (below 12mm) i.e., the inner regions of the workspace, PID showed accuracy comparable to DMRAC.

The developed controller was also tested for the Distant Point protocol and Adjacent Point protocol presented in Section 4.1. The developed hybrid controller was successful in achieving the desired accuracy of less than 0.2mm by switching to the best performing controller. The comparisons of the performance of PID controller, DMRAC and the hybrid controller are shown in Figure 6.43-Figure 6.44 and Figure 6.46-Figure 6.47.

In the Distant Point protocol, PID controller performed poorly in the outer regions (radius $\geq 8\text{mm}$) of the robot workspace. The poor performance of PID can be attributed to the greater movement by the lead screw and hence greater friction when moving to the outer part of the workspace. Also due to the presence of the coupling medium in the HIFU jig, as the rotational motion becomes greater, the change in moment of inertia is also greater. DMRAC showed a 22% better accuracy compared to PID controller in the outer regions of the workspace and almost same accuracy in the inner regions of the robot workspace. DMRAC is able to handle these dynamic changes much better.

In the Adjacent Point protocol, both PID controller and DMRAC performed equally well. This may be due to the fact that in this protocol, the subsequent target points are adjacent to each other, less than or equal to 1mm apart. Hence, the amount of movement required and the amount of change in the HIFU jig mass distribution are very minimal. Since PID controller is

considered the default controller, in the event where both controllers are performing equally well, the PID controller is chosen as the controller in the feedback loop.

Validation

The integrated system which consists of the dynamic deformation tracker and the hybrid supervisory controller was validated using the FUSBOT-NS end-effector as the robot and ultrasound imaging system as the intra-operative modality. The tumour deformation was simulated with the help of a motorized jig which gave the brain phantom a linear motion of upto 40mm in the direction of gravity with dynamic speeds (0.524mm/second, 0.393mm/second and 0.262mm/second). This speed of motion is quite fast compared to the displacement tumour in an actual neurosurgery. The integrated robotic system was able to track the brain phantom satisfactorily with a mean error of 0.267mm and maximum error of 1.9mm with a lag of 0.62seconds. This lag is due to the computation time required for the deformation estimation and also for the controller computations. Since, the actual brain tissue deformation is much slower than the speed used for the brain phantom, this testing can be considered as a worst case scenario.

The hierarchical hybrid control strategy along with the brain tissue deformation tracking algorithm provides a common control strategy for non-invasive neurosurgical robots. It tackles the issue of degrading targeting accuracy due to the intra-operative brain tissue deformation. This common control framework would greatly enhance the speed of development of non-invasive neurosurgical robots as the developers can focus more on the optimization of the framework rather than develop customized control strategies from scratch. It would also help in the formulation of a common safety guidelines for image guided non-invasive neurosurgical robots.

7.2 Major Contributions

In this work, a novel common control strategy for non-invasive neurosurgery robotic systems which takes into account the dynamic intra-operative brain shift was proposed implemented and tested. Currently available non-invasive neurosurgery robotic systems track only the skull

position and orientation during surgery. This is based on the assumption that there is a fixed spatial relationship between the target and the patient's skull. This assumption fails for non-invasive surgical modalities such as High Intensity Focused Ultrasound (HIFU), which are mechanical waves, as they further aggravate the problem of brain shift. Hence, tracking of the deformation intra-operatively is extremely important for accurate treatment delivery in non-invasive neurosurgery.

The two main requirements for the control strategy proposed that were addressed in this research project were- one is the speed of intra-operative brain shift estimation and the accuracy of treatment delivery based on updated target position information.

Image control- Dynamic Deformation Tracking

For the dynamic deformation tracking, a two-stage strategy was implemented. Template matching algorithm was used to estimate the rigid component of the deformation i.e., the displacement and CPD algorithm, a point based non-rigid image registration algorithm, was used to estimate the non-rigid deformation of the tissue. The computation time of the strategy was a critical factor in the implementation of this strategy as the deformation needs to be estimated as frequently as possible due to the continuous and unpredictable nature of brain shift. Experimental setup, to simulate the clinical scenario, was devised for the testing of the dynamic deformation tracking scheme using ultrasound imaging. The test trials showed that the computation time was an average of 72.7seconds. The expected deformation in this time (72.7 seconds) is very low, especially in the case of non-invasive surgery, as brain shift is a slow process. The strategy devised in this work greatly enhances the speed of deformation estimation as the first stage provides fast gross position information of the targeted brain abnormality as well as the dislocation information, which speeds up the target delineation process in the second stage. In current practices, the estimation takes about 4-5minutes to capture the intra-operative images using MRI/CT images [10]. In commercially available neuronavigation systems such as z-touch BrainLab [123], the surgeon has to manually scan hundreds of points in a predefined manner on the patient's head to collect surface points and to register it. This is time-consuming and error-prone compared to the strategy tested in this

work where the feature is delineated and points gathered through automatic segmentation. Using the strategy proposed and implemented in this work, it is possible to track the deformation in almost real-time (every 1-2minutes) thereby reducing the possible inaccuracies in treatment delivery due to intra-operative brain shift.

Robotic control- Hierarchical Hybrid Supervisory Controller

A three layer hierarchical hybrid controller with PID controller and DMRAC as the constituent controller with an estimator-based supervisor was developed as the control strategy for non-invasive neurosurgical robots. The efficacy of this control scheme was experimentally tested and verified. In this control scheme, PID controller and DMRAC compete against each other where the supervisor in the hybrid structure chooses between PID controller and DMRAC based on their estimated potential performances. This would ensure that the accuracy of the robot will be in the acceptable limit throughout the operation and in all regions of the robot workspace.

The controllers used in this hybrid controller are non-model based controllers. Model-based controllers would be much more effective in cases where the robot geometry and robot operation environment is known. However, this is not true in the case of surgical robots as environments in which surgical robots work, which is the operation theatre, is highly unstructured and unpredictable due to factors such as human intervention and is difficult to model. Moreover, in the case of neurosurgery, the nature of the movement of the target (brain abnormalities) is dynamically changing and hence adds to the unpredictability of the surgical environment. Therefore, by using non-model based controllers, the robotic control strategy proposed in this work is independent of the robot structure and environment in which the robot works.

Finally, a surgical protocol is proposed for non-invasive robotic neurosurgical using the control strategy for the control of the robot and the two-stage deformation tracking strategy for the near real-time intra-operative estimation of the tissue deformation.

7.3 Future Work

1. ***Common safety protocol:*** The development of an action protocol in the event of failure so as to ensure the robot fails in a controlled manner and at the same time allowing the surgeon to continue from where the surgery had stopped would be an extremely important extension to the work presented here. Along with the common control strategy devised in this work, a common safety protocol for non-invasive neurosurgical robots could be formulated. This would bring a consensus on the minimum safety requirements for neurosurgical robots and thus would greatly help in reduce the development time of the neurosurgical robots.
2. ***Use of high quality brain phantom for laboratory testing:*** It is important to test and improve the dynamic deformation tracking strategy using high quality brain phantom which are close to the real case scenario. The brain phantom should be deformable so as to recreate the non-linear deformation brain undergoes during surgery. The brain phantom presented in [124] is made of PVAc with plastic tubes as blood vessel and can be deformed by placing under the phantom a catheter attached to a balloon. This phantom was found to be useful in deformation estimation using MRI and US imaging with accuracy less than 1mm.
3. ***Validation using in vivo ultrasound images:*** In laboratory settings, the deformation of the phantom is highly controlled and predictable. The dynamic deformation tracking strategy should be tested using ultrasound images taken during the course of a neurosurgical procedure for validation for clinical scenario.
4. ***Use of 3D ultrasound imaging:*** The implemented deformation algorithm was tested only in 2D ultrasound images. The testing of the control strategy using deformation estimation using 3D US imaging would be desirable.

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LIST OF PUBLICATIONS

V J Kuruvilla, M.C.C., M T Tan, G Seet, S Chauhan, *Focus Ultrasound Based Minimally Invasive Robotic Neurosurgery* in *UIA Symposium 2009*: British Columbia.

V J Kuruvilla, S Chauhan, *Real time Estimation of Brain Tissue Dislocation and Deformation- A Phantom Study*, *Journal of Medical Imaging and Health Informatics* 2013 (**Accepted**).

V J Kuruvilla, S Chauhan, *Hybrid Supervisory Control for Biomechatronic Systems for Non-Invasive Neurosurgery* 2013 (*in preparation*)

APPENDIX A

Deformation Estimation Error and Computation time data

Down-sampling by 2

CPD RESULTS

Point Set	No. of points	Computation time (seconds)		p2p error before (mm)	p2p error after (mm)
		trial 1	trial 2		
1	462	26.79	28.24	1.65	0.512
2	462	18.08	19.17	3.03	0.92
3	462	7.08	7	7.767	3.59
4	356	10.37	12.23	6.889	4.75
5	488	9.82	7.89	13.99	2.67
6	540	15.63	16.1	6.88	3.03
7	489	21.96	20.52	2.369	1.056
8	462	26.44	22.9	1.419	0.486
9	416	3.73	5.78	6.11	3.677
10	416	36.28	31.34	8.476	3.4
11	458	5.47	6.2	0.341	0.339
12	458	4.81	4.72	6.495	1.61

Down-sampling by 4

CPD RESULTS

Point Set	No. of points	Computation time (seconds)		p2p error before (mm)	p2p error after (mm)
		trial 1	trial 2		
1	231	9.0629	28.24	1.65	0.52
2	231	4.938	19.17	3.03	0.945
3	231	2.136	7	7.767	3.742
4	178	4.311	12.23	6.889	4.74
5	244	3.507	7.89	13.99	2.73
6	270	4.611	16.1	6.88	3.17
7	245	4.218	20.52	2.369	1.2
8	231	5.433	22.9	1.419	0.691
9	231	1.335	5.78	6.11	3.684
10	231	6.353	31.34	8.476	3.41
11	229	1.982	6.2	0.341	0.56
12	229	3.217	4.72	6.495	1.62

TPS-RPM RESULTS

Point Set	No. of points	Computation time (minutes)		p2p error before (mm)	p2p error after (mm)
		trial 1	trial 2		
1	923	26.2	26.2	1.65	0.433
2	923	25	25.7	3.03	0.779
3	923	25.5	25.5	7.767	3.3
4	713	20	22.1	6.889	4.52
5	976	23.4	20.9	13.99	2.31
6	1080	30.5	28.2	6.88	2.47
7	978	22.7	22.6	2.369	0.57
8	923	25.4	26.3	1.419	0.39
9	831	22.6	23.1	6.11	3.51
10	831	23.4	24.2	8.476	2.85
11	915	21.9	22	0.341	0.26
12	915	23	24.1	6.495	1.49