Miniature robot system for keyhole neurosurgery

A thesis submitted in fulfillment of the requirements for the degree of Master of Science

By

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November 13, 2005
To Ayelet
Acknowledgements

In this interdisciplinary research, medical doctors, computer scientists, physics experts and commercial companies are cooperating for the successful birth of a new medical hi-tech technology. Before presenting my work, I would like to thank to those people and companies which contributed to the success of this project.

To my supervisor, Prof. Leo Joskowicz, for supporting and guiding me through the stages of this research and writing of this thesis, and for sharing me with his insights in the field of computer aided surgery.

To my colleague, Moti Freiman, for the productive and pleasant period during which we worked together, and for his good advices and ideas.

To colleagues and past colleagues in the Computer-Aided Surgery and Medical Image Processing Laboratory: Ziv Yaniv, Harel Livyatan, Dotan Knaan, Pavel Kats, David Sariashvily, Yaron Ostrovsky-Berman, Aviv Hurvitz, and Noa Dimentman, for creating a pleasant place to work in, and for their ideas and sights.

To Dr. Yigal Shoshan, for guiding me through medical issues, teaching me about neurosurgery and about the way a surgeon thinks, and for his full cooperation and help.

To Prof. Felix Umansky, for his support and interest.

To Prof. Moshe Shoham, for advising and helping me with mechanical issues and with the MARS robot.

To Eli Zehavi and Mazor Surgical Technologies for contributing the MARS robot, and for their interest.

To Dr. Luis Ibanez, from the ”Insight Segmentation and Registration Toolkit” (ITK), for sharing me with his insights about image segmentation.

To Prof. Gabriel Taubin, for his method and help on curvature’s estimation.

To Arik Degani from Mabat, and to Dr. Tamir Shalom from CogniTens, for their help in scanning our faces.

For this research I used extensively the Visualization ToolKit (VTK) and consulted with the VTK and ITK communities. I thank those organizations and the people in these communities for their help.
Abstract

This thesis presents a novel image-guided system for precise automatic targeting in keyhole minimally invasive neurosurgery. The system consists of a miniature robot fitted with a mechanical guide for needle/probe insertion. Intraoperatively, the robot is directly affixed to a head clamp or to the patient skull. It automatically positions itself with respect to predefined targets in a preoperative CT/MRI image following an anatomical registration with an intraoperative 3D surface scan of the patient facial features.

We describe an efficient method that extracts head’s outer surface from CT/MRI images, and aligns it with a 3D facial scan in the operating room. Then, the spatial relation between preoperative data and intraoperative situation is calculated.

We also describe an intraoperative robot positioning module, which helps the surgeon place the robot base close (within 5mm) of its planned position.

In our experiments, the proposed method proved to be accurate, fast and robust, with an average accuracy of 1mm RMS error.

We conclude the thesis with suggestions for improvements to our methods and future work.
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Chapter 1

Introduction

Surgery is the science and practice of treating injuries and disease by cutting the body open and removing or mending part of it. At present, with the rise of computers, interdisciplinary research groups are developing new methods and tools in the growing field of Computer Aided Surgery (CAS). The goal of CAS is to enhance the surgical process with computer capabilities such as three dimensional displays, planning, real-time intraoperative monitoring and localization, and more. Today, surgeons use the computer for training, diagnosing, planning and feedback, enjoying the benefits of the computer’s imaging, graphical and computing abilities [65, 66].

1.1 Minimally invasive surgery

Large incisions enable surgeons to see and manipulate the pathological tissue directly. The significant damage done to organs in the surgical path causes pain to the patient, entails long recovery time, and causes complications due to surgical trauma. The goal of Minimally Invasive Surgery (MIS) is to prevent unnecessary trauma by reducing the size of incisions to a few centimeters or less. The benefits of reduced trauma, less pain and shorter recovery time, make MIS the technique of choice of many surgeons around the world [16, 18]. Free-hand MIS suffers from reduced dexterity, limited perception, increased error, and longer procedure time. Fortunately, contemporary computer aided technologies help reduce these limitations and enable a better access, dexterity, perception and accuracy [17].

1.2 Keyhole neurosurgery

Neurosurgery is a surgery of the brain. Whenever feasible, neurosurgery should be MIS, to minimize patient discomfort, improve cosmetic results and shorten hospital stay and recovery time [19].

A keyhole neurosurgery is a MIS technique of the brain, in which a needle or a
probe is inserted through a slot to the pathological tissue and is manipulated. The insertion path should be as short as possible to avoid unnecessary brain damage. The benefits are minimization of brain retraction and reduced damage to normal tissue [19, 24].

Operations performed with the keyhole neurosurgery approach include:

1. **Brain biopsy with a needle**
   Biopsy is the process of removing tissue from living patients for diagnostic examination. Brain needle’s biopsy is a biopsy of material obtained from the brain by means of a hollow needle inserted through the body and into the affected part [59]. This type of biopsy is widely used for sampling cerebral lesions, brain stem lesions, multiple small lesions, or for patients medically unable to tolerate general anesthesia for open biopsy [62].

2. **Catheter placement**
   Catheter placement is a fixation of a tubular instrument that allows the passage of fluid from or into a body cavity or channel [59, 60]. It is useful for drainage of lesions, indwelling catheter placement for intratumoral chemotherapy, radioactive implants for interstitial radiation brachytherapy, and shunt placement for cyst drainage [62]. One example is the Ommaya reservoir treatment, in which a permanent ventricular catheter interfaces a small bag with oncological drugs (Ommaya reservoir). This solution increases drugs efficiency, as the drug is placed directly to the site and remains there, thereby eliminating the need of repeated surgery. [63, 64].

3. **Electrode placement**
   An implantation of electrical terminal specialized for a particular electro-chemical reaction, elicits response in a muscle, nerve, or other excitable tissue, or causes an augmenting action upon any function or metabolic process [59]. In neurosurgery, electrode placement is an effective treatment for epilepsy, parkinsonism, dystonia and hemiballismus [62]. Parkinsonism, for example, is a progressive disorder of the central nervous system, in which a degeneration of dopamine-producing neurons, and the severe reduction of dopamine in the basal ganglia brings about most of the symptoms: tremor, impaired motor performance, rigid facial muscles, impaired walking, poor posture, autonomic dysfunction, and sensory complaints [61]. When anti-parkinsonian drugs have no effect, electrical stimulation at the damaged area, should be used to relieve Parkinson symptoms [62].

4. **Evacuation of intracerebral homorrhage**
   Intracerebral homorrhage is bleeding into the substance of the cerebrum, usually in the region of internal capule by the rupture of the lenticulostriate artery [59].
1. **Pre Imaging**
   Prepare patient for imaging

2. **Preoperative**
   a. Images acquisition
   b. Planning
   c. Preoperative calculations

3. **Intraoperative**
   a. Preparation
   b. Localization
   c. Insertion
      i. Planned path
      ii. Planned depth
      iii. Planned force
   d. Operation

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| A keyhole neurosurgery targeting instrument, enables the removal of the hemorrhage. Stereotactic technique uses Archimedes screw device with adjunctive urokinase or recombinant tissue-plasminogen activator [62]. |

5. **Minimal invasive craniotomy**
   In this neurosurgery technique, a small opening into the skull (craniotomy) enables the whole operation procedure [59], in which ventricular-type catheter, a blunt biopsy needle or introducer are typical tools [62]. Keyhole neurosurgery system targets the tools and guidance their insertion during the operation.

Following a careful analysis of the most common keyhole neurosurgery procedures in the literature and at the Hadassah Hospital University, Jerusalem, Israel, we compiled a protocol scheme that describes a typical keyhole neurosurgery procedure, as shown in Table 1.1.

1. **Pre-imaging**
   Patient preparation before imaging is necessary for several techniques to align the preoperative images with the situation in the operating room. In the stereotactic frame technique, four screws are affixed to the skull. Because those screws are fixed during the preoperative and intraoperative stages, they form a reference frame and achieve alignment. A special frame is attached to the screws during the preoperative imaging, and enables the alignment between the preoperative images and the intraoperative situation. For navigation, skin markers are attached to the patient’s head before imaging. In the operating room, the
alignment is achieved by contact based registration on the markers and anatomical landmarks. At least four landmarks (markers or anatomies) are necessary for contact based registration.

2. Preoperative

The preoperative stage consists of acquiring the patient images, planning the surgery and calculating some relevant information before the surgery. After acquiring patient’s images from CT or MRI, the surgeon plans the surgery with the assistance of the computer. Usually, target points and the possible trajectories are selected on preoperative images. Additional preoperative operations are performed: when a stereotactic frame is used, the registration information is extracted from the preoperative images. When a navigation system is used, landmarks locations for contact based registration are defined.

3. Intraoperative

The intraoperative stage consists of:

(a) Preparing the patient and the operating room for keyhole neurosurgery.

Patient preparation includes sterilization and head fixation. Stereotactic surgery, navigation system or robotic unit requires operating room preparation and manual frame adjustment, tracker localization or robot placement, respectively.

(b) Locating the correct entry point and trajectory.

After a stereotactic frame has been adjusted according to the preoperative images and plan, it is attached to the skull screws and adjusted to the predefined target and in the right trajectory.

Other techniques require to perform intraoperative registration with the preoperative data. Most navigation systems, for example, require following a contact based registration protocol in the operating room. In this protocol, the surgeon manually aligns the markers and anatomical landmarks defined in the preoperative images and their locations, as obtained from the tracking system in the operating room.

(c) Inserting the needle or the probe.

A needle insertion support instrument is necessary for surgeries that require high accuracy, precise small movements, needle fixation, depth control, or force feedback. For example, in Deep Brain Stimulation (DBS) the surgeon looks for a suitable location for electrode implantation with the help of a special needle that measures electrical activity. When the appropriate location is reached, an electrode is implanted. The movements of the measuring needle are small and delicate, the electrode implantation requires accurate repetitive abilities and needle fixation; It is impossible to make those procedures by hand, even for an experienced surgeon. Mechanical guidance instruments, such as the EasyTaxis™, support shift...
avoidance, needle fixation and depth control other mechatronic tools also enable precise small movements, depth control and force feedback [17].

(d) *Pathological tissue manipulation*
Biopsy, aspiration, evacuation and stimulation are routine operations on pathological tissues, as described in section 1.2.

Stages (a) to (d) are repeated as necessary, either to treat other tissues or due to complications.

We will use this generic protocol as the basis of comparison between existing solutions.

1.3 Goals and specifications

The goal of this thesis is to design a practical, automatic, target and guidance system for keyhole neurosurgery. The goals are to have a system that is accurate, fast-to-align, robust, safe, inexpensive and intuitive to use.

Safety can be achieved readily, as the miniature robot is already used for spine surgeries, and has proved to be safe. The miniature robot is less expensive than navigation systems or other medical robotics units. Following a careful analysis of the most common keyhole neurosurgery procedures, we compiled the following specifications for the first three factors.

The system requirements are:

1. **Accuracy:** A target registration error of 1.5 mm on average (2 mm worst case).
   An angle error of 1.5 degrees on average (2 degrees worst case).

2. **Time:** The registration process takes at most 10 minutes in the operating room.

3. **Robustness:** The registration between the preoperative data and the intraoperative situation succeeds at least 95% of the time within the specified error and speed.

Typical characteristics of the MRI image: pixel size of $1.1 \times 1.1 \text{mm}^2$ or less.

1.4 System and method overview

The system consists of a miniature robot fitted with a mechanical guide for needle/probe insertion. The key idea is to establish a common reference frame between the preoperative CT/MRI image and the intraoperative patient head and robot locations with an intraoperative 3D surface scan of the patient’s facial features. Once this registration has been performed, the transformation that aligns the planned and actual robot targeting guide location is computed. The robot is then automatically
positioned and locked in place so that its targeting guide axis coincides with the entry point/target axis (Figure 1.1).

The system hardware consists of: 1) the MARS robot and its controller; 2) a custom robot mounting base, a targeting guide, and a registration jig; 3) an off-the-shelf 3D surface scanner (accuracy of 0.3mm or less and density of 10 samples cm$^2$ or more), and; 4) a standard PC. MARS is a sterilizable 5 × 5 × 8cm$^3$, 250-gram six-degree-of-freedom parallel manipulator with work-volume of about 15cm$^3$ and accuracy of 0.1mm. It operates in semi-active mode; when locked, it is rigid and can withstand lateral forces of up to 10N. The adjustable robot mounting jig attaches the robot base to either the head immobilization frame or to skull-implanted pins. The system software modules are: 1) preoperative planning; 2) intraoperative execution; 3) surface scan processing; and 4) three-way registration.

The surgical protocol is as follows. A preoperative, marker and frame-less CT/MRI image of the patient is acquired. Next, with the preoperative planning module, the surgeon defines on the image the entry points and target locations, and determines the robot mounting type (head clamp or skull) and the desired robot location. Intraoperatively, guided by a video-based intraoperative module, the surgeon places the robot approximately in its planned location. When the robot is mounted on the head frame, the robot base is attached to an adjustable mechanical arm affixed to the head clamp. When mounted on the skull, two 4mm pins screwed under local anesthesia
into the skull and the robot mounting base is attached to them. Next, the registration jig is placed on the robot mounting base and a surface scan showing both the patient forehead and the registration jig is acquired. The registration jig is then replaced by the robot with the targeting guide on it, and the three-way registration module automatically computes the offset between the actual and the desired targeting guide orientation. It then positions and locks the robot so that the actual targeting guide axis coincides with the planned needle insertion trajectory. On surgeon demand, the system automatically positions the robot for each of the predefined trajectories.

The proposed system is a MIS technique, as the two possible robot mounting techniques are: 1) on a frame, which is fixed to the patient (like in navigation systems); and 2) on the patient’s head, with two screws drilled to the patient skull in the operating room (same invasiveness as mounting the patient to a navigation system frame). For sterility, a special plastic sleeve that covers the robot is currently available and already in use for spinal surgeries. Preoperative data to intraoperative situation registration is possible via patient’s facial landmarks, as at current navigation systems, preoperative to intraoperative registration procedures are based on facial landmarks alignment on both datasets. The MARS robot has proved to be practical for targeting and guidance tasks in the spine, therefore, the proposed neurosurgery targeting and guidance system is also expected to be practical.

The suggested system advantages are: 1) better accuracy, as the robot mounted near or on the surgical site; 2) low cost with respect to other systems, as the robot and some 3D scanners are inexpensive; 3) simple and intuitive usage, as the system supports automatic targeting and guidance; 4) short registration process, because it is fast and automatic; and 5) robustness, as the registration algorithm is robust.

1.5 Novel aspects

The proposed system improves several aspects of existing methods and successfully overcomes the major drawbacks of current systems: accuracy, cost, simplicity, speed and robustness.

For accuracy, the miniature robot is mounted near or on the surgical site. The robot structure and close proximity to the surgical site results in better accuracy [11].

For cost effectiveness, the system consists of the relatively inexpensive MARS robot and an off-the-shelf 3D scanner. In this work we used a high accuracy scanner to validate our methods and to explore the system’s accuracy boundaries. Because this scanner is expensive, cheaper scanners with lower accuracy (0.2-0.5 mm) will be considered in later systems.

For simplicity, the registration transformation between preoperative data and intraoperative situation is completely automatic. The surgeon only has to fix the robot with a registration jig on the patient’s head or on the frame, and scan the face and jig with a 3D scanner. Unlike other techniques, such as stereotactic frame or navi-
gation system, no patient preparation is required in the pre-imaging step (step 1 in table 1.1).

For speed, the transformation between the 3D scanner facial surface and the corresponding CT/MRI surface is computed by first computing a coarse correspondence between them in a short time (one minute for landmarks extraction). This correspondence is then refined with robust Iterative Closest Point (ICP) registration [14], which is performed between a small (1,000–3,000) subset of the surface scan points and the CT/MRI points on the face/ear surface to reduce computation time.

For robustness, the coarse correspondence computation is independent of the spacial properties of the datasets, as it is computed from the extracted landmark eye points in both datasets. The refinement done with a robust version of ICP, which converged accurately in all our experiments.

Given the small robot workvolume and the lack of anatomical landmarks on the skull, a coarse positioning module is necessary to avoid deviations of 10-20mm or more from the planned position. We implemented an intraoperative robot positioning module to help the surgeon place the robot base close (within 5mm) of its planned position.

The surface registration algorithm, which finds the transformation between the face surface scanner cloud of points and the corresponding CT/MRI surfaces, was implemented and validated in two experiments. In the first experiment, three pairs of CT and MRI images, which acquired from different patients, were used. The MRI images were used for the planning and the surgery of those patients. A 3D surface reconstruction of the face had extracted from CT images, and is used to simulate a 3D scan. For the second experiment, the author and a colleague acquired MRI scans of their heads following a routine neurosurgery imaging protocol at the Hadassah hospital. The facial surface scans acquired with eye-safe of-the-shelf 3D laser scanner. The author and colleague tried different facial expressions that patients in this situation may have. The situations we expressed are: 1) sleep; 2) awake and calm; 3) awake and disturb. Some MRI images, with disturbed expression, were to noisy and useless.

Given the small robot workvolume and the lack of anatomical landmarks on the skull, a coarse positioning module is necessary to avoid deviations of 10-20mm or more from the planned position. We implemented an intraoperative robot positioning module to help the surgeon place the robot base close (within 5mm) of its planned position. A conference paper version of this thesis was published in [37].

For related ongoing work, [38, 39].

1.6 Thesis organization

The thesis consists of seven chapters. Chapter 2 is a survey of the current state of the art in keyhole neurosurgery, and describes the MARS robot. Chapter 3 introduces the mathematical background about transformations, describes the proposed keyhole neurosurgery protocol, the preoperative data to intraoperative situation registration
protocol and algorithm, and the preoperative images to intraoperative scan registration algorithm. Chapter 4 describes the generation of head’s outer surface from preoperative images and the automatic anatomical landmarks detection algorithm. Chapter 5 describes the coarse positioning module for the positioning of the robot base. Chapter 6 describes the experiments and results of the registration algorithm. Chapter 7 concludes with summary and topics for future work.
Chapter 2

Literature overview

This chapter reviews existing systems for keyhole neurosurgery and presents the MARS robot. Section 2.1 reviews the current state of the art in keyhole neurosurgery and examines each method benefits and limitations. The protocols for each technique are described as observed in operations at the Hadassah hospital. Section 2.2 reviews the MARS miniature robot for surgical applications, and discusses its benefits and limitations.

2.1 State of the art for keyhole neurosurgery

In this section we describe three keyhole neurosurgery techniques: 1) Stereotactic frames; 2) Navigation systems and mechanical arms; and 3) Robotic systems. Intraoperative imaging systems are also described in the last part of this section, as they can be used to enhance each of these techniques.

1. Stereotactic frames

Initiated by Clarke and Horsley in 1906, the stereotactic methodology has been employed by neurosurgeons to map image space onto physical space. In this technique, the mapping is achieved by mounting the frame based on anatomic landmarks, such as external canals and inferior orbital rims. Since the frame is identically mounted on each subject based on those landmarks, previously obtained maps are used to place electrodes, make lesions, and take tissue samples [28, 56, 57].

Stereotactic frames solve the localization and path insertion guidance issues (steps 3b and 3c-i in Table 1.1). Optionally, when a needle insertion device is attached to the stereotactic frame they also perform the insertion depth or force control (steps 3c-ii and 3c-iii in Table 1.1). Using this approach the protocol is as follows (stages which are not relevant have been omitted):

1. Acquire the preoperative MRI data.
2. Make the preoperative plan on MRI data.
Typical protocol scheme for stereotactic neurosurgery.

Figure 2.1: A typical protocol scheme for stereotactic neurosurgery. After acquiring preoperative data (usually MRI) and planning the surgery the surgeon (1) implants screw to the patient’s skull, (2) attaches special registration frame on the screws and (3) acquire registration images (usually CT). With the help of the computer, some (4) registration calculations are done. In the operating room the (5) stereotactic frame adjusted manually by the surgeon and then (6) attached to the screws and surgery can be performed.

3. Implant screws in the skull and attach special frame to the patient.

4. Acquire the preoperative CT image.

5. Calculate the stereotactic frame position adjustment values based on CT and MRI images, and on the preoperative plan.
6. Adjust the stereotactic frame as calculated.

7. Attach the stereotactic frame to the patient.

8. Perform surgery according to the guidance of the stereotactic frame.

The advantages of using this approach are: 1) this is a tested, standard method of treatment; 2) it is relatively accurate (< 2\text{mm}); 3) it provides a rigid and robust support and guidance for needle insertion, and; 4) it has relative low cost with respect to other systems.

The disadvantages of using this approach are: 1) non-intuitive, mathematically intensive; 2) does not localize structures in real time; 3) poor acceptance by patients and neurosurgeons, and; 4) plan cannot be changed.

2. Navigation systems

Navigation systems show the surgeon the location of the hand-held tool with respect to the preoperative CT or MRI image onto which targets have been defined. Usually, the preoperative data is aligned with the intraoperative situation by contact based registration via skin markers or screws attached to the patient’s skull before scanning. In a recent innovation of Medtronic, a 3D facial scanning of the patient in the operating room enables to perform a contact-free registration. Navigation systems provide a solution to the localization (step 3b in Table 1.1). When augmented with a tracked mechanical arm, such as the EasyTaxis arm, they also provide a solution for path and depth insertion guidance (steps 3c-i and 3c-ii in Table 1.1) [29, 30, 31, 32, 33, 28]. BrainLAB (www.brainlab.com) and Medtronic (www.medtronic.com) are commercial companies that sell neurosurgery navigation systems.

With these systems, the typical protocol is as follows (Figure 2.2) (stages which are not relevant have been omitted):
1. Attach markers to the skin of the patient (optional).
2. Acquire the preoperative MRI or CT data.
3. Make the preoperative plan.
4. Align preoperative data to the intraoperative navigation system using contact based registration, or surface registration.
5. Attach mechanical arm for mechanical support during the surgery.
6. Perform surgery according the feedback of the navigation system, and, optionally, with mechanical guidance.

The advantages of using this approach are: 1) it provides real-time feedback during positioning and needle insertion; 2) modification of the plan is possible during the surgery; 3) not restricted insertion angles, and; 4) rigid and robust support and guidance for needle insertion (with the assistance of a mechanical arm).

The disadvantages of using this approach are: 1) most systems require head immobilization; 2) requires hand-eye coordination; 3) it requires line-of-sight; 4) require manual registration which consumes time and requires learning; 5) it might require manual passive arm positioning, which can be time consuming, less accurate, and requires learning, and; 6) it has relative high cost with respect to other systems.

3. Robotics systems

Robotics systems are frameless and have the potential to address the intraoperative localization, guidance, and insertion steps with a single system. They provide steady positioning, mechanical guidance, and great stability and accuracy. They can be floor standing, mounted on the table, or hanging from the ceiling.

Using this approach several methods can be used for the registration of the preoperative data with the intraoperative situation. Instead of describing the whole protocol for each possible scheme only the registration methods will be discussed.

Two commercial systems that are currently available are: The NeuroMate robot by Integrated Surgical Systems, (ISS), Sacramento, USA (http://www.robodoc.com/eng/neuromate.html), and the PathFinder robot by Armstrong Healthcare Limited, (ALH), High Wycombe, UK (http://www.armstrong-healthcare.com).

NeuroMate is an image-guided, computer-controlled, robotic system for brain surgeries. It also includes a pre-surgical planning workstation. The NeuroMate System positions, orients and manipulates the operating tools within the surgical field exactly as planned by the surgeon on the image planning workstation. The system interacts with the surgeon during surgery and adapts to the changes required during the surgery. The first generation NeuroMate system required the use of cumbersome and painful head frames that are traditionally used in the current manual techniques.
for brain surgeries. The proprietary "frameless" technique of ISS altogether eliminates the need for cumbersome and painful head frames. In the frameless mode, registration is performed using an ultrasonic system. A single base is implanted into the skull and during imaging a detachable four spokes fiducial system with MR visible markers at the end of each spoke is mounted to the base plate. Then, planning software module is used to identify targets and plan trajectories. The positions of the four markers of the fiducial system are identified in the dataset. An ultrasound microphone array with an identical geometry to the fiducial system is attached to the base plate and an array of four ultrasound emitters is attached to the working arm of the robot. The position of the microphones is then co-registered to the position of the fiducials in the pre-operative dataset. Using this information the robot is aligned to the pre-operative data. A clinical study has assessed the accuracy of this system and showed that an application accuracy of 2 mm or less could be achieved in routine clinical practice. The robot can support payload of up to 5 kg [10].

The PathFinder is an image-guided six axes robot that provides a stable, accurate tool position platform for neurosurgery. PathFinder removes the need for a stereotactic frame and its associated calculations. Fiducial markers are attached to the patient’s skin before acquiring the preoperative data. After scanning, the preoperative images are loaded into the PathFinder preoperative planning software. The software automatically detects the markers and defines coordinate system according to them. The surgeon selects the targets and entry points and saves the plan. In the operating room the robot is placed at about 50 cm from the patient head. The patient head is held in a Mayfield clamp, to which the robot is also rigidly attached. The plan file is loaded into the robot. The robot arm sweeps a camera over the patient’s head at a range of about 750 mm. The visually distinctive fiducial markers are automatically located in each framegrab of the camera. By combining a series of framegrabs it is possible to estimate the location of the fiducial markers in robot coordinates. These
Camera

(a) PathFinder neurosurgical robot   (b) PathFinder tip with small camera for registration

Figure 2.4: (a) The PathFinder neurosurgical robot and (b) a close up to the robot’s tip. A small camera used to align the preoperative data with the intraoperative situation.

marker locations are then matched by the robotic system to the marker locations in the preoperative images. This way the preoperative data is aligned with the intraoperative situation [34]. A recent research reported an average overall application error accuracy of 1.0 mm [35].

The advantages of using existing robotics systems are: 1) the modification of the plan is possible during the surgery; 2) there is no restriction on inserted angles; 3) it provides rigid and robust support and guidance for needle insertion, and; 4) automatic registration.

The disadvantages of using existing robotics systems are: 1) robot size: cumbersome in operating room, limits patient access; 2) requires head immobilization, and; 3) relative high cost with respect to other systems.

4. Intraoperative imaging

The premise of stereotaxy, navigation and robotics, is that preoperative imaging provides information which is sufficient to guide the surgeon during the course of the surgery. There are several cases in which this premise is strained, if not invalidated. These cases include: major shifts in the brain due to heavy retraction or the removal of fluid, poor visualization of desired structures due to size or nature of the tissue, or inexact determination by CT/MRI images of tumor margins or epilepsy foci. In these cases, intraoperative imaging greatly enhances the surgical process and allows the improved identification and localization of a structure or a lesion boundary. Intraoperative imaging, be it ultrasound, endoscopic evaluation, or MRI, provides information
as to the present position of structures of concern and the relative position of surgical instruments, regardless of any changes or manipulations of the brain [25, 58]. Intraoperative imaging and interactive, image guided surgery are not competitive processes but complementary ones. Each technique can provide information the other cannot.

2.2 A miniature robot for surgical applications

Prof. Moshe Shoham and his group at the Technion have developed an accurate MiniAture Robot for Surgical applications (MARS). MARS is a sterilizable $5 \times 5 \times 8 \text{cm}^3$, 250 gram, six degree of freedom parallel manipulator with work-volume of about $10\text{cm}^3$ and accuracy of 0.1 mm [11]. Currently this robot is in use for orthopedic procedures in several sites around the world. This miniature robot does not consume space in the operating room and yet enables automatic precise targeting and guidance. Mounting the robot directly on the patient’s bony structure, near the surgical site, avoids patient’s immobilization. To support needle insertion feedback a mechanical stopper or a microdrive should be attached to the robot’s arm. Because of the limited working volume of the robot, a rough positioning module is required.

The advantages of using the miniature robot are: 1) no size or line-of-sight problems; 2) potentially, it is more accurate than existing robots; 3) the modification of the plan is possible during the surgery; 4) insertion angles are not restricted; 5) it provides rigid and robust support and guidance for needle insertion; 6) automatic registration; 7) relative low cost with respect to other systems, and; 8) no patient immobilization required.

The main disadvantage of using the miniature robot is its limited working volume.
Since in many keyhole neurosurgery operations a needle or a probe is inserted accurately according to a preoperative plan, the MARS robot, which had designed for similar applications in the spine, seems to be a good match. The required working volume for this type of surgery is small, therefore the limited working volume of the robot is not a problem.
Chapter 3

Problem statement and methods

This chapter presents the registration problem framework and an overview of the proposed system. Section 3.1 provides theoretical background for transformations. Section 3.2 defines the problem to solve. Section 3.3 describes a keyhole neurosurgery protocol with the miniature robot and a 3D surface scanner. Section 3.4 presents the three-way registration protocol and algorithm. Section 3.5 lists the main challenges.

3.1 Background for transformations

This work deals with points that relate to variety of coordinate systems, each defined by the position of its origin, the directions of its axes and its scale factor. We follow the notation used in [40] to present a point in a given coordinate system and represent a transformation from one coordinate system to another. Let \( A \) and \( B \) be coordinate systems, and let \( p^A \) represent a point \( p \) in \( A \). A transformation \( T^B_A \) converts \( p^A \) to coordinate system \( B \): \( p^B = T^B_A \cdot p^A \). Given two transformations \( T^B_A \) from \( A \) to \( B \) and \( T^C_B \) from \( B \) to \( C \), a new transformation \( T^C_A \) from \( A \) to \( C \) is obtained by composing \( T^C_A = T^C_B \cdot T^B_A \). The inverse transformation from \( C \) to \( A \) is denoted by \( T^A_C = (T^C_A)^{-1} \).

A spatial transformation \( T \), consisting of translation, rotation and scale factor, is obtained by:

\[
\tilde{p} = T \times p = s(R \times p + t)
\]

where \( \tilde{p}, p \in \mathbb{R}^3 \) represent the same point in different coordinate systems, \( t \in \mathbb{R}^3 \) represents a translation, \( R \), is a \( 3 \times 3 \) matrix of real numbers represents rotation and \( s \in \mathbb{R} \), and \( s > 0 \) represents the scale factor.

3.2 Problem definition

The problem consists of finding a transformation \( T^\text{or}_{\text{pre}} \) that relates the preoperative images with the intraoperative robot coordinate frame in the operating room. With
the help of a 3D surface scanner the transformation $T_{or}^{pre}$ is computed as a composition of two transformations: $T_{scan}^{pre}$, the transformation between the preoperative images and the 3D intraoperative scan coordinate systems, and $T_{or}^{scan}$ the transformation between the 3D intraoperative surface scan and the miniature robot coordinate systems. Therefore the transformation chain is:

Equation 3.2.1

$$T_{or}^{pre} = T_{or}^{scan} \cdot T_{scan}^{pre}$$

Because three components are involved to obtain the transformation $T_{or}^{pre}$, we will use the term **three-way registration** as the process of estimating the transformation between the preoperative images and the intraoperative robot coordinate systems via a 3D surface scan, which is acquired in the operating room.
The registration algorithm that computes the transformation $T_{\text{pre}}^{\text{scan}}$ will be described in section 3.4. The registration algorithm that computes the transformation $T_{\text{tor}}^{\text{scan}}$ is out of the scope of this thesis (see [67] for details).

3.3 Keyhole neurosurgery protocol

This section presents a surgical protocol for keyhole neurosurgery using a miniature robot and a three-way registration method. The protocol scheme is as described following the outlined in Table 1.1.

1. **Pre Imaging**
   
   No pre imaging preparations are required

2. **Preoperative**
   
   (a) Data acquisition - acquire preoperative images
   (b) Planning - plan the surgery
   (c) Preoperative calculations - extract head’s outer surface from preoperative images and find anatomical landmarks.

3. **Intraoperative**
   
   (a) Preparation
      
      i. Rough positioning and attachment of the robot’s base and the registration jig.
      
      ii. 3D scanning of the patient’s face and robot’s registration jig.
      
      iii. Three-way registration calculation.
   
   (b) Localization - The miniature robot targets automatically, based on the surgery plan and the three-way registration.
   
   (c) Insertion
      
      i. Robot’s mechanical support eliminates shift errors, and ensures correct insertion path.
      
      ii. For the control of insertion depth or force, a special instrument should be attached to the robot.

The accuracy of the MARS robot, the preoperative data and the 3D surface scanner are sufficient for keyhole neurosurgery. The three-way registration method and its accuracy are thus one of the critical components of the system.
3.4 Three-way registration

This section presents the three-way registration protocol and algorithm.
The protocol is as follows:

**Preoperative**

1. Acquire preoperative data (MRI or CT).
2. Extract head’s outer surface.
3. Find anatomical landmarks.

**Intraoperative**

1. Attach the robot’s base to the patient’s skull or to a frame which is fixed relative to the patient. The base location should be close to the surgical site, so the miniature robot can target that point. A real time, coarse positing system is used for this task.
2. Attach the registration jig on the base.
3. Scan the patient face with a 3D surface scanner.
4. Find anatomical landmarks (on the 3D scan).
5. Estimate $T_{scan}^{pre}$ - the alignment between the preoperative data and the 3D scan.
6. Estimate $T_{or}^{scan}$ - the alignment between the 3D surface scan and the robot home position.
7. With Equation 3.2.1, compute $T_{or}^{pre}$ - the transformation between the preoperative data coordinate system and the intraoperative robot coordinate system.

Once the transformation is found, the registration jig should be replaced with the robot. Then, the robot positions itself automatically, using $T_{or}^{pre}$, to the predefined targets and trajectories as planned in the preoperative images.

We now present a method to estimate accurately $T_{pre}^{scan}$, which is the transformation between the preoperative data and the 3D scan.

To minimize the total registration time and achieve robustness, a two-phase registration approach is proposed. The first phase is fast, coarse registration, achieved by finding correspondence between anatomical landmarks in both datasets. The second phase is slower, accurate registration achieved with an improved version of the Iterative Closest Point (ICP) algorithm. Since the extraction of the anatomical landmarks does not depend on the position or orientation of the surfaces, the registration method is robust and converges with any initial spatial difference between the datasets.
Because this algorithm matches the facial surfaces, we will use the term surface registration as the process of estimating $T_{\text{scan}}^{\text{pre}}$ with the following algorithm.

**Registration algorithm**

**Input:**

1. A set of 2D preoperative images with scanning information (such as voxel size) of patient’s head, denoted by $\text{Images}_{\text{MRI}}$.

2. A mesh that represents the face of the same patient, denoted by $\text{Surface}_{\text{scanner}}$.

**Algorithm:**

1. Extract the outer surface from $\text{Images}_{\text{MRI}}$, denoted by $\text{Surface}_{\text{MRI}}$.

2. Extract four anatomical landmarks of both $\text{Surface}_{\text{MRI}}$ and $\text{Surface}_{\text{scanner}}$ and pair them.

3. Perform closed-form registration according to the anatomical landmarks pairs and apply the resulting transformation, $\hat{T}^{\text{Scanner}}_{\text{MRI}}$, on $\text{Surface}_{\text{MRI}}$. Let the result be denoted by $\hat{\text{Surface}}_{\text{MRI}}$. Then we have:

   **Equation 3.4.1**
   
   $\hat{\text{Surface}}_{\text{MRI}} = \hat{T}^{\text{Scanner}}_{\text{MRI}} \cdot \text{Surface}_{\text{MRI}}$.

4. Perform Iterative Closest Point registration between $\hat{\text{Surface}}_{\text{MRI}}$ and $\text{Surface}_{\text{scanner}}$, and apply the resulted transformation, $T_{\text{ICP}}$, on $\hat{\text{Surface}}_{\text{MRI}}$. Let the result be denoted by $\text{MriSurface}^{\text{Scanner}}$. Then we have:

   **Equation 3.4.2**

   $\text{MriSurface}^{\text{Scanner}} = T_{\text{ICP}} \cdot \hat{\text{Surface}}_{\text{MRI}}$.

5. Define the over-all transformation, $T^{\text{Scanner}}_{\text{MRI}}$, to be $T^{\text{Scanner}}_{\text{MRI}} = T_{\text{ICP}} \cdot \hat{T}^{\text{Scanner}}_{\text{MRI}}$. Notice that according to equations 3.4.1 and 3.4.2 we get the equality:

   **Equation 3.4.3**

   $\text{MriSurface}^{\text{Scanner}} = T^{\text{Scanner}}_{\text{MRI}} \cdot \text{Surface}_{\text{MRI}}$.

**Output:**

1. $T^{\text{Scanner}}_{\text{MRI}}$ - The transformation from MRI coordinate system to scanner coordinate system.

2. $\text{MriSurface}^{\text{Scanner}}$ - The 3D surface extracted from MRI data in the scanner coordinate system.

The data flow of the registration protocol and algorithm are described in Figure 3.2.
3.5 The main challenges

The registration process consists of four main tasks:

1. Outer surface extraction from preoperative images.
2. Anatomical landmarks extraction.
3. Closed form registration.
4. Iterative Closest Point registration.

Since the registration algorithm should be robust, accurate and fast, each one of these tasks should be optimized.

1. Outer surface extraction

At first glance, because the outer surface extraction from preoperative images is applied at the preoperative stage, time is not a major issue. However, a fast method enables the flexibility of surgical planning, changing reconstruction parameters and planning close to operation time. Chapter 4 describes a fast and accurate outer surface reconstruction method from preoperative head images. The key idea is to segment the non-material areas and then extract the outer surface of the head as the border between air and tissue.
2. Anatomical landmarks detection

Anatomical landmarks pairs enable the fast, coarse registration. The anatomical landmarks used in this work are the four horizontal edge points of the eyes. The extraction of the landmarks is performed in two steps: 1) estimate curvatures on the mesh with Taubin’s method; and 2) find anatomical landmarks with a costume search algorithm. Chapter 4 describes the anatomical landmarks extraction algorithm in more details.

3. Closed form registration

The closed form algorithm builds a set of equations according to a set of points pairs and approximate its solution, which is the required registration transformation. This method is fast, but because the landmarks pairing is not perfect the resulting transformation might not be accurate.

4. Iterative closest Point (ICP) registration

The ICP algorithm attempts to pair the points of two sets and to perform closed form registration iteratively. The algorithm will converge only if the two points sets are close enough, and have similar orientation and scale factor. Using the anatomical landmarks pairing for initial guess in the ICP algorithm, grantees the algorithm’s convergence. To make the ICP algorithm faster, the pairing is done only on a small subset (200 – 3,000) of points sampled uniformly from the original meshes. The resulting overall transformation accuracy using a subset of points, was the same as using the whole set of points. The overall accuracy was measured on all the points.
Chapter 4

Head surface extraction and anatomical landmarks detection

The creation of the outer head surface model from preoperative head data is essential for preoperative-intraoperative registration. This chapter presents an accurate and fast method, which consists of two steps: 1) head’s segmentation; and 2) head’s surface reconstruction. Surface reconstruction uses a version of the Marching Cubes algorithm: a fast algorithm for rendering isosurfaces in volumetric data. Since the skin surface intensity has high variance, simple isosurface thresholding methods are not applicable. To solve this problem, we developed a new segmentation method to separate the head from the outer zones. Section 4.1 describes the segmentation algorithm. Section 4.2 describes the 3D outer surface extraction algorithm.

4.1 Head segmentation algorithm

The head outer surface is the surface between the surrounding air and the voxels inside the head. Applying the Marching Cubes algorithm [21] to extract the outer head’s surface will produce the outer head’s surface, but will also include the ear’s tunnel and interior head’s halls. The additional surfaces have variant curvature values, which difficult the automatic landmarks detection. Because the inner halls and the outer surface are separated components, taking the right connected component will eliminate the inner halls. Unfortunately, the ears tunnels are in the same connected component as the outer surface.

To solve these problems, we have developed a special segmentation algorithm. At first, the segmentation algorithm creates binary images according to a low-intensity threshold. It then performs open and close operations to fill the ears tunnels. Since the close and open operations creates an offset of the original images (Figure 4.1), the output of the segmentation algorithm returns the threshold filtered binary image and the binary image after cleaning the ears tunnels. The first binary image enables a latter offset correction. Below, is a formal description of the segmentation algorithm.
Figure 4.1: For each MRI scan (a) a binary image is produced using a threshold (b). Close and open 3D image operations are used to close the ears tunnels (c).

**Segmentation algorithm**

**Input:** A set of 2D preoperative images with scanning information (such as pixel size, slice thickness, color depth, etc.,) of patient’s head, denoted by $Images_{MRI}$.

**Algorithm:**

1. Given a separation threshold, create a new binary image for each slice in $Images_{MRI}$, such that:
   
   $Binary_{slice}(x, y) = \begin{cases} 
   1 & slice(x, y) > \text{threshold} \\
   0 & \text{otherwise} 
   \end{cases}$

2. Build a 3D volume from $\{Binary_{slice}\}$, denoted by $Binary-Image$.

3. Perform 3D close operator on $Binary-Image$, denoted by $Binary-Image-Closed$.


**Output:**

1. $Binary-Image$ - a binary image of the head, before ear’s tunnel removal.

2. $Binary-Image-After-Ears-Tunnel-Removal$ - a binary image of the head, after ear’s tunnel removal.
Figure 4.2: Surface reconstruction from 2D MRI images (a). As seen at the interior view (b), the algorithm deleted inner structures and the ear’s tunnels.

4.2 Head’s outer surface reconstruction algorithm

This section describes an accurate and fast reconstruction method for the head outer surface. The method applies Marching Cubes surface reconstruction algorithm, on both binary images, either before or after ears tunnels filling. This results the head’s outer surface, but also the ear’s tunnels and head inner halls surfaces. The inner surfaces removal is easy, as the head outer surface is the largest connected component and therefore is straightforward to segment. Deleting all surfaces, beside the largest connected component, on both datasets, results in two surfaces: 1) accurate head outer surface with ears tunnels; and 2) head outer surface without ears tunnels with an offset. The offset, occurred by close and open operations, changes the image scale and close small halls or tunnels. Using a robust ICP algorithm to compute the offset, the surface without ears tunnels is re-scaled, and represents accurately the head’s outer surface (Figure 4.2). The changes in the halls and tunnels does not effect the robust ICP method. Below, a formal description of the head’s surface extraction algorithm. The description includes the segmentation step to clarify the role of the segmentation in the algorithm.

Surface extraction algorithm

**Input:** A set of 2D preoperative images with scanning information (such as pixel size, slice thickness, color depth, etc.,) of the patient’s head, denoted by $Images_{MRI}$.

**Algorithm:**
1. Perform a segmentation on $Images_{MRI}$. Let the segmentation algorithm outputs be denoted by $Binary-Image$ and $Binary-Image-After-Ears-Tunnel-Removal$ - a binary images of the head, before or after ear’s tunnel removal, respectively.

2. Apply the Marching Cubes algorithm on both surfaces: $Binary-Image$ and $Binary-Image-After-Ears-Tunnel-Removal$. Let the two resulting surfaces sets be denoted by $MC_{binary}$ and $MC_{removed-ears}$, respectively.

3. Extract the largest connected component from each surfaces set: $MC_{binary}$ and $MC_{removed-ears}$. Let the two resulting surfaces be denoted as $MC_{binary}$ and $MC_{removed-ears}$, respectively.

4. Perform ICP registration between $MC_{binary}$ and $MC_{removed-ears}$. Let the resulting transformation be denoted as $T_{binary \rightarrow removed-ears}^{\text{ICP}}$.

5. Apply $T_{binary \rightarrow removed-ears}^{\text{ICP}}$ on $MC_{removed-ears}$. Define $Surface_{MRI}$ as:

\[
Surface_{MRI} = T_{binary \rightarrow removed-ears}^{\text{ICP}} \cdot MC_{removed-ears}.
\]

Output: $Surface_{MRI}$ - the outer surface of the head.

A crucial step of the surface registration, as described in section 3.4 is automatic eyes landmarks detection. For robustness, the algorithm should detect the correct landmarks for at least 95% of facial surface inputs. Because the landmarks are used for rough registration, the accuracy should not be very high, but sufficient for the ICP algorithm to converge. The algorithm should be fast, as it will be used in the operating room. The following sections describe a fast curvature based method for extraction of the eyes horizontal edges from preoperative head’s outer surface or intraoperative facial scan. Section 4.3 introduces the curvature’s mathematical background, following [41] and [42]. Section 4.4 consists of two parts: 1) curvature estimation methods overview; and 2) description of Taubin’s algorithm, the method used in this thesis. Section 4.5 describes the automatic eyes landmarks detection algorithm.

4.3 Background for curvatures

1. Curvature

Let $X(t)$ be a parameterization of a twice differentiable curve. Then, the curvature of $X(t)$, signed as $\kappa(t)$ defined as:

\[
\kappa(t) = \frac{|\dot{X}(t) \times \ddot{X}(t)|}{|X(t)|^3}
\]

Intuitively, the curvature is a measure of the deviation of a curve from a straight line.
2. Normal curvature

Let \( X(u,v) \) be a twice differentiable, parametric surface. Then, the **unit normal vector** is defined by:

\[
N(u, v) = \frac{X_u \times X_v}{|X_u \times X_v|},
\]

where \( X_u = \frac{\partial X}{\partial u} \) and \( X_v = \frac{\partial X}{\partial v} \).

The **normal curvature**, denoted by \( \kappa_n \), defined as:

\[
\kappa_n = \frac{L(\ddot{u})^2 + 2M(\ddot{u}, \dot{v}) + N(\ddot{v})^2}{E(\dot{u})^2 + 2F(\dot{u}, \dot{v}) + G(\dot{v})^2},
\]

where \( E = X_u \cdot X_u, F = X_u \cdot X_v, G = X_v \cdot X_v, L = X_{uu} \cdot N, M = X_{uv} \cdot N \) and \( N = X_{vv} \cdot N \).

Intuitively, the normal curvature of a surface is the curvature of the intersection curve between the surface and the plane containing the surface normal and the tangent vector.

3. Principle, Gaussian and Mean curvatures

The **principle curvatures**, denoted by \( \kappa_1(u_0, v_0) \) and \( \kappa_2(u_0, v_0) \), is defined on a twice differentiable parametric surface, \( X(u, v) \), as the maximum and minimum normal curvatures at \( X(u_0, v_0) \), respectively.

**Euler’s theorem:**

\[
\kappa_n = \kappa_1 \cos \theta^2 + \kappa_2 \sin \theta^2,
\]

where \( \theta \) is the angle between the first principal direction and the tangent direction.

The **Gaussian curvature**, denoted by \( K \), is defined as:

\[
K = \kappa_1 \cdot \kappa_1
\]

The **Mean curvature**, denoted by \( H \), is defined as:

\[
H = \frac{\kappa_1 + \kappa_2}{2}
\]

4.4 Curvature estimation methods on triangular meshes

The differential invariant properties, such as Gaussian and mean curvatures, are well established in the Computer Vision literature and extensively used for segmentation, recognition and registration [53, 54]. In this work, facial curvature’s estimations from triangular meshes are used to detect eyes landmarks and perform surface registration in the operating room. Therefore, the curvature estimation method should be fast,
as it is used in the operating room, and reliable, to enable the anatomical landmarks detection.

For this thesis we consider five methods for the estimation of the principal curvatures, as compared by Surazhsky T. et el. [55]. We assume that the given triangular mesh approximates a smooth, at least twice differentiable, surface. Next, we provide a short overview of each method. Then, we describe Taubin’s algorithm in more details, as this is the estimation method which we use.

The five algorithms for curvature estimation are:

1. **Paraboloid fitting:** This algorithm approximates a small neighborhood of the mesh around a vertex \( v \) by an osculating paraboloid. The principal curvatures of the surface are considered to be identical to the principal curvatures of the paraboloid [43, 44, 45].

2. **Circular fitting:** This algorithm constructs circles through a vertex \( v \), and a pair of neighbors of \( v \), \( v_i \) and \( v_j \), such that the angle between vectors \((v_i - v)\) and \((v_j - v)\) is close to \( \pi \). By selecting at least three pairs of such neighbors the principle curvatures and principle directions extracted using Meusnier’s theorem [46, 47].

3. **Gauss-Bonnet:** From simple trigonometry we can conclude that the sum of angles between any successive edges from a vertex \( v \) to its immediate neighbors is equal to the sum of angles between outer angles defined by the neighbors of \( v \). The algorithms in [45, 50] use this trigonometric fact and the Gauss-Bonnet theorem [48, 49] to extract directly the mean and Gaussian curvatures.

4. **Watanabe and Belyaev:** A consequence of Euler’s theorem is that the integration of the normal curvature and its second power over all possible tangent plane directions enables the extraction of the mean and Gaussian curvatures [51]. To approximate the integration value on a triangular mesh, the trapezoid approximation can be used.

5. **Taubin:** This algorithm is based on the construction of a quadratic form at each point, \( p \), of the polyhedral surface, \( S \), and then computing eigenvalues and eigenvectors of the resulting form [52]. In this algorithm, the quadratic form associated with a point is expressed as an integral, construct in time proportional to the number of neighborhood points. If this number is small the algorithm will finish in short time. We use this algorithm for construction of anatomical landmarks detection method, and it found to be reliable and fast.

**Taubin’s algorithm:**

We describe Taubin G. algorithm next [52]. The first part introduces the mathematical background of the method. The second part describes a practical algorithm for curvature’s estimation.
Let $S$ be a given triangular mesh approximates at least twice differentiable surface. If the normal curvature function, $\kappa_p(\cdot)$, is a quadratic form, it satisfies the identity:

$$\kappa_p(T) = \left( \begin{array}{c} t_1 \\ t_2 \end{array} \right)^t \left( \begin{array}{cc} \kappa_{11}^p & \kappa_{12}^p \\ \kappa_{21}^p & \kappa_{22}^p \end{array} \right) \left( \begin{array}{c} t_1 \\ t_2 \end{array} \right),$$

where $p$ is a point on the surface, and $T = t_1 \cdot T_1 + t_2 \cdot T_2$ is a tangent vector to $S$ at $p$. $\{T_1, T_2\}$ is an orthonormal basis of the tangent space to $S$ at $p$. If $\kappa_{12}^p = \kappa_{21}^p = 0$, then $T_1$ and $T_2$ are the principle directions of $S$ at $p$, and $\kappa_{11}^p$ and $\kappa_{22}^p$ are the principal curvatures of $S$ at $p$.

Let us define $T_\theta$, a unit length tangent vector, as:

$$T_\theta = \cos \theta \cdot T_1 \sin \theta \cdot T_2,$$

where $T_1$ and $T_2$ are the orthonormal principal directions of $S$ at $p$.

According to equations 1 and 2 above

$$\kappa_p(T_\theta) = \kappa_{11}^p \cdot \cos^2 \theta + \kappa_{22}^p \cdot \sin^2 \theta,$$

Let us define the symmetric matrix

$$M_p = \frac{1}{2\pi} \int_{-\pi}^{\pi} \kappa_p(T_\theta) T_\theta T_\theta^t d\theta,$$

Another possible notation of $M_p$ is:

$$M_p = T_{12}^t \left( \begin{array}{cc} m_{11}^p & m_{12}^p \\ m_{21}^p & m_{22}^p \end{array} \right) T_{12}$$

where $T_{12} = [T_1, T_2]$, a $3 \times 2$ matrix.

Taubin shows that $m_{12}^p = m_{21}^p = 0$. Therefore the two remaining eigenvectors of $M_p$ are the principal directions $T_1$ and $T_2$. According to the corresponding eigenvalues
the principal curvatures are:

\[ \kappa_{p}^{11} = 3m_{p}^{11} - n_{p}^{22}, \quad \kappa_{p}^{22} = 3m_{p}^{22} - n_{p}^{11} \]

Therefore, the principal curvatures can be estimated by estimating the matrix \( M_{p} \).

The algorithm is as follows:

**Input:** A triangular mesh that approximates at least twice differentiable surface \( S \).

**Algorithm**

For each vertex \( v_{i} \in S \):

1. Estimate the normal vector, \( N_{v} \), as the normalized weighted sum of the normals of the incident faces, with weights proportional to the surface area of the faces.

2. Estimate \( M_{p} \) with a weighted sum over the neighborhood \( V_{i} \):

\[
\tilde{M}_{p} = \sum_{v_{j} \in V_{i}} w_{ij} \kappa_{ij} T_{ij} T_{ij}^{T}
\]

where \( T_{ij} \) is the normalized projection of the vector \( v_{j} - v_{i} \) onto the tangent plane of \( S \) at \( v_{i} \), \( \kappa_{ij} \) is an approximation of the directional curvature at direction \( T_{ij} \), and \( w_{ij} \) is a weight proportional to the sum of the surface area of all the triangles that are incident to both vertices \( v_{i} \) and \( v_{j} \). \( \kappa_{ij} \) approximated as follows

\[
\kappa_{ij} = \frac{2N_{v_{i}}(v_{j} - v_{i})}{\|v_{j} - v_{i}\|^{2}}.
\]

3. Compute \( T_{1} \) and \( T_{2} \) - the principal directions, according to \( \tilde{M}_{p} \), Householder transformation and Givens rotation.

4. Compute \( \kappa_{v_{i}}^{11} \) and \( \kappa_{v_{i}}^{22} \) - the principal curvatures, according to equation 6.

**Output:** A set of principal curvatures and directions, \( \{ \kappa_{v_{i}}^{11}, \kappa_{v_{i}}^{22}, T_{1}^{v_{i}}, T_{2}^{v_{i}} \} \in S \)

### 4.5 Automatic eyes landmarks detection algorithm

To estimate the mean curvature, three large vertices groups with high curvature value are examined. There is one group for each ear, and one group for the eyes and for the nose zones. The eyes and nose vertices set consists of three subsets: 1) left eye; 2) right eye; and 3) nose and noise. Those measurements are the base for the eyes landmarks detection algorithm. A method, which classifies vertices into neighborhood groups, has been incorporated into the algorithm. We first describe this classification method, and then the eyes landmarks detection algorithm.

The vertices neighborhood grouping method (VNG) creates vertices sets, such that all vertices in the same set are contained in a sphere of fixed radius. The vertices sets are then sorted according to their size to detect anatomical zones represented by vertices sets of known size. For example, the ears and eyes vertices groups are the
larger ones in the head’s curvature’s threshold vertices. Below is a formal description of the method:

**Vertices neighborhood grouping method (VNG)**

**Initialization**

1. Set the number of vertices sets to zero, \( n = 0 \).
2. Set \( V \) to be a dynamic array of size \( n \), such that for \( 1 \leq i \leq n \), \( V[i] \) has three fields: 1) \( V[i].v \) - a vertex that represents this set of vertices; 2) \( V[i].vertices \) - all the vertices in this set; and 3) \( V[i].size \) - the number of vertices in this set.

**Input**

1. \( H \) - a set of vertices.
2. \( d \) - neighborhood radius.

**Algorithm**

1. For each vertex \( u \in H \):
   
   (a) \( belong = false \)
   
   (b) For \( i = 1 \ldots n \)
   
   i. If \( \|V[i].v - u\| < d \)
   
   ii. \( belong = true \)
   
   iii. \( V[i].vertices = V[i].vertices \cup u \)
   
   iv. \( V[i].v = \frac{V[i].v \cdot V[i].size + u}{V[i].size + 1} \)
   
   (c) If \( belong = false \)
   
   i. \( n = n + 1 \)
   
   ii. \( V[n].v = u \)
   
   iii. \( V[n].vertices = u \)
   
   iv. \( V[n].size = 1 \)

2. Sort array \( V \) in descending order, according to the group’s size.

**Output:** \( V \) - an array of vertices, grouped according to their neighborhood, and sorted in descending order.

The input for the algorithm consists of two components: 1) a set of vertices; and 2) a neighborhood radius. The algorithm checks, for each input vertex \(- u \), if there is
already a group of vertices, which created by the algorithm and its center is close to vertex \( u \) (step 1.b), with respect to the neighborhood radius. If such a group exists, then add \( u \) to this group of vertices. If such a group is invalid, then create a new group, with one vertex - \( u \) (step 1.c). This way, all the vertices are classified into neighborhood groups. After classifying all vertices, the algorithm sorts the groups of vertices in descending order according to their size. The output of the algorithm is a sorted array of vertices sets.

We use Taubin’s method for curvature estimation, the vertices neighborhood grouping method (VNG) and the anatomical properties, for the next eye’s landmarks detection algorithm.

Eyes landmarks detection algorithm

Initialization

1. Set eyes and nose set, \( \text{EyesNose} = \emptyset \).
2. Set eyes and ears set, \( \text{EyesEars} = \emptyset \).

Input

1. \( S \) - a triangular mesh.
2. \( \text{type} \) - indicates if the mesh represents the whole head or only the face.
3. \( \text{CURV} \) - is a relative curvature threshold value, \( 0 \leq \text{CURV} \leq 1 \).
4. \( \text{FAR} \) - is the size of the VNG distance parameter used to separate between the eyes and the ears.
5. \( \text{CLOSE} \) - is the size of the VNG distance parameter used to detect each eye.

Algorithm:

1. Apply Taubin’s method for mean curvature’s estimation on \( S \).
2. Find maximum and minimum curvature’s values, denoted as \( \max(S) \) and \( \min(S) \), respectively.
3. For each vertex \( v \in S \)
   \[
   \frac{\text{curvature}(v) - \min(S)}{\max(S) - \min(S)} > \text{CURV}, \text{ then } \text{EyesEars} = \text{EyesEars} \cup v.
   \]
4. If \( \text{type} = \text{head} \) then
   (a) Compute \( V = \text{VNG}(H = \text{EyesEars}, d = \text{FAR}) \).
   (b) Compute \( i \in \{1, 2, 3\} \), such that \( V[i] \) represents the eyes and nose vertices set.

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(c) $EyesNose = V[i]$

else

$EyesNose = EyesEars$

5. Compute $V_2 = VNG(H = EyesNose, d = CLOSE)$.

6. $a_1 = V_2[1].v$ and $a_2 = V_2[2].v$ represents two eyes landmarks.

7. Create a vector $v_{eyes} = 2 \cdot (a_2 - a_1)$.

8. The rest anatomical landmarks points, $a_3, a_4 \in S$, are the closest to $a_2 + v_{eyes}$ and $a_1 - v_{eyes}$, respectively.

Output: Eye’s landmarks set $\{a_1, a_2, a_3, a_4\}$.

The input for the algorithm consists of five components: 1) a triangular mesh; 2) a flag that indicates if the mesh represents the face or the entire head’s surface; 3) $CURV$ - a relative curvature threshold value; 4) $FAR$- the value of the VNG distance parameter used to separate between the eyes and the ears, and; 5) $CLOSE$- the value of the VNG distance parameter used to detect each eye. In our experiments $CURV = 0.9$, $FAR = 3.5$, and $CLOSE = 0.7$. At first, Taubin’s method is applied to estimate curvature values of the surface, then the curvature’s map is filtered with a threshold, which eliminates vertices that their curvature is in the 90% lower curvature’s values (the comparison assumes uniform distribution). If the input surface represents the head’s outer surface, then a VNG method is applied to the filtered vertices, resulting with the ears and eyes-nose zones (Figure 4.4(a)-(b)), which is located at the three largest vertices sets in the vertices sets set that returned by the method. To decide which vertices set represents the eyes-nose zone, among the three sets, we use two anatomical observations: 1) the distance between the ears zones is larger than the distance between each ear zone and the eyes-nose zone; and 2) the distances between each ear zones and eyes-nose zone are similar. If the input surface represents the outer head’s surface, then the eyes-nose vertices group is as calculated. Else, the eyes-nose vertices group is as computed by the facial surface threshold filter, because there is no need to filter the ears. Computing VNG with a lower radius on facial filtered points, results in two eyes landmarks (Figure 4.4(c)), as the first two vertices sets centers are two landmarks of the eyes. To compute two more landmarks, a vector added to each of the two landmarks in opposite directions. Then the vector is projected onto the surface, and its tip created a new landmark (Figure 4.4(e)). The vector size and direction is decided according to measurements done on preoperative images, so it will reach near the outer horizontal edge of each eye.
Figure 4.4: Views of head surface, during the procedure of the landmarks search. (a) and (b) side and frontal views of head surface, augmented with three spheres that represent the ears and eyes-nose zones, as detected by the algorithm. (c) frontal view of the head surface, augmented with two spheres, the centers represent two eyes landmarks, as detected by the algorithm. (d) frontal view of facial surface, augmented with the final four eyes landmarks as detected by the algorithm.
Chapter 5

Intraoperative robot positioning

The intraoperative robot positioning module helps the surgeon place the robot base close (within 5mm) of its planned position both for skull and frame-mounted cases. Given the small robot workvolume and the lack of anatomical landmarks on the skull, this coarse positioning is necessary to avoid deviations of 10mm or more from the planned position. These deviations can severely restrict or invalidate altogether the preoperative plan. Section 5.1 describes the concept of the proposed robot positioning module. Section 5.2 describes an implementation of this module.

5.1 Method

The goal is to compute the robot base planned position with respect to a video camera image so that the robot base model can be projected on the video or virtual images at its desired planned position. The video camera is directly mounted on the 3D surface scanner and is pre-calibrated, so that the transformation between the two coordinate systems, $T_{\text{video}}$ is known in advance. A 3D surface scan of the face is acquired and matched to the geometric face model with the same method as described in section 3.4. This establishes the transformation between the preoperative plan and the scanner, $T_{\text{scanner}}$. By composing the two transformations, we obtain the transformation between the preoperative plan and the video, $T_{\text{video}}^{\text{plan}}$.

The proposed scheme is described formally in Figure 5.1. Define three coordinate systems: 1) preoperative plan, denoted as $\text{plan}$; 2) intraoperative 3D surface scanner, denoted as $\text{scanner}$, and; 3) intraoperative video camera, denoted as $\text{video}$. Using the transformation notations as described in Chapter 3, we define $T_{\text{scanner}}$ - the transformation from the preoperative plan coordinate system to the intraoperative 3D surface scanner coordinate system, and $T_{\text{scanner}}^{\text{video}}$ - the transformation from the intraoperative 3D surface scanner coordinate system to the intraoperative video camera coordinate system. The transformation from the preoperative plan coordinate system to the intraoperative video camera coordinate system, denoted by $T_{\text{plan}}^{\text{video}}$ is calculated as follows:
Figure 5.1: Intraoperative robot positioning computation.

\[ T_{\text{video}} = T_{\text{video}}^\text{scanner} \cdot T_{\text{scanner}}^\text{plan}. \]

\( T_{\text{scanner}}^\text{plan} \) is calculated as described in section 3.4. \( T_{\text{video}}^\text{scanner} \) is calculated as follows (Figure 5.2). A custom registration jig establishes a common reference frame between the 3D surface scanner and the video camera. Define \( T_{\text{jig}}^\text{scanner} \) - the location of the jig in the 3D surface scanner coordinate system, and \( T_{\text{jig}}^\text{video} \) - the location of the jig in the coarse navigation system coordinate system. We can calculate the transformation from the intraoperative 3D surface scanner to the intraoperative video camera as follows:

\[ T_{\text{scanner}}^\text{video} = (T_{\text{jig}}^\text{video})^{-1} \cdot T_{\text{jig}}^\text{scanner}. \]

The registration jig described in detail in [38, 67]. It is attached with a special card which is tracked by the video camera. Since the video camera is fixed to the 3D surface scanner, the transformation \( T_{\text{video}}^\text{scanner} \) is calculated only once.

Three types of output are available with the proposed module: 1) Virtual Reality (VR), in which the real-time location of the positioning jig is virtually displayed on the preoperative data; 2) Augmented Reality (AR), in which the real-time location of the positioning jig and/or the preoperative data is virtually displayed on the real-time video images, and; 3) wireframe figure, in which the real-time location of the positioning jig is displayed on a special graphical interface which indicates the tool location.

5.2 Implementation

We implemented a module that shows the surgeon a real-time, augmented reality and virtual reality images (Figures 5.4 and 5.5). The augmented reality image consists of a video image of the actual patient skull and the positioning jig, and, superimposed
Figure 5.2: A special registration jig is used as a common reference frame between the 3D surface scanner and the intraoperative video camera.

on it, a virtual image of the same jig indicating the robot base in its desired location. The virtual reality image consists of a virtual image of the positioning jig in its desired location, virtual head surface which extracted from the preoperative image, and a virtual positioning jig in its current location. The surgeon can then adjust the position and orientation of the positioning jig until it matches the planned location. The inputs are the preoperative plan, the geometric models of the robot base and the patient face, the real-time video images, and a face scan.

Since the 3D surface scanner is not currently available, the alignment of the video camera to the preoperative images is done with a graphical user interface. Once we have a 3D surface scanner, a complete prototype of the system, as described in the previous section, will be implemented.

The following hardware is used for the robot base positioning module: 1) off-the-shelf web camera; 2) 60 × 60mm cards with special patterns for video tracking, and; 3) a PC, 2.4Ghz, 1 GB RAM, under Windows XP.

We use the ARToolkit software toolkit. ARToolkit is a collection of software libraries for augmented reality applications, in which virtual computer graphics images are superimposed on the real world image. This toolkit uses a web camera for real time tracking of special cards and overlay the video images with virtual computer graphics images. We use the ARToolkit to display the virtual image of the positioning jig on a video image of the actual patient skull and positioning jig (augmented reality display). The ARToolkit tracking module is also used to display the tools locations
in the preoperative virtual environment (virtual reality display).

Figure 5.3: The real world situation (a) is aligned with the virtual display using the implemented graphical user interface (b).

Figure 5.4: Real world situation (a) is displayed in virtual world (b) with the implemented coarse positioning module.

The implemented graphical user interface enables the user to define the location of the head in the video camera coordinate system. A special tracking card is fixed to the head. The user can then position a virtual tracking card on a virtual head surface that extracted from the patient preoperative images, so the virtual head and card have similar spatial relation as the actual head and card (Figure 5.3). This provides a registration transformation between the preoperative image and the fixed tracking card.
In the virtual reality display, an additional mobile card is tracked. The transformation between the mobile card and the fixed one is calculated with the ARToolkit coarse positioning module, and the transformation between the fixed card and the preoperative image is calculated previously. Concatenating those transformations the transformation between the mobile card and the preoperative image is calculated, and virtually displayed (Figure 5.4).

In the augmented reality display, no additional calculations are necessary, and the virtual positioning jig image is displayed on the video image of the actual head and positioning jig (Figure 5.5).
Chapter 6

Experimental results

We have implemented a prototype of the entire system as described in section 1.4. To test the accuracy of the surface registration, we carried two in-vitro experiments. Section 6.1 describes the materials that are used to test the proposed surface registration. Section 6.2 describes the experiments we applied to test our system and their results. Section 6.3 summarizes and discusses the experimental results.

6.1 Materials

The following materials were used to test the surface registration:

1. **CT images**: In the first experiment, a 3D facial surface was extracted from CT images to simulate surface scanner output. The CT scans are $512 \times 512 \times 30$ pixels$^3$ with voxel size of $0.7 \times 0.7 \times 1.0$ mm$^3$ from which $15,000 - 20,000$ surface points were extracted.

2. **3D Surface scanner**: In the second experiment, we used the Konica Minolta Vivid 910 3D digitizer. It consists of a laser source and a camera. It supplies a 3D cloud of points obtained from the scanned surface. A software, supplied with the scanner, enables editing the points and triangulating them, for a mesh creation. For our experiment, each scan was acquired during several seconds and contains 35,000 - 50,000 points, with manufacturer defined accuracy of 0.1 mm or better.

3. **MRI images**: In both experiments, MRI images were acquired with the standard neurosurgery imaging protocol used in Hadassah. In the first experiment, the MRI images were $256 \times 256 \times 80$ pixels$^3$ with voxel size of $1.1 \times 1.1 \times 2.0$ mm$^3$ from which $150,000 - 300,000$ surface points were extracted. In the second experiment, the MRI scans were $256 \times 256 \times 200$ pixels$^3$ with voxel size of $0.93 \times 0.93 \times 0.5$ mm$^3$ from which $110,000 - 140,000$ surface points were extracted.
4. **Computer:** We compute surface registration with a PC, 2.4Ghz, 1 GB RAM, under Windows XP. Figure 6.1(b) shows a screen dump of the registration software, which was developed for this research.

### 6.2 Experiments results

To validate our surface registration algorithm, we conducted two experiments: 1) CT/MRI registration, in which clinical MRI images were aligned with facial surface that extracted from clinical CT images of the same patient; and 2) laser scans/MRI registration, in which clinical MRI images were aligned with the facial surface points that acquired with a laser scanner.

In the first experiment, we used two pairs of clinical MRI and CT images of the same patient. The CT images included stereotactic frame attached to the skull, as the patients were treated with this technique. Those images were manually segmented, and only the head remained. Then, a surface scanning was simulated by shooting imaginary rays from outside to the face zones. The head outer surface extraction from MRI images was calculated as described in Chapter 4, and took about 120 sec. Extraction of anatomical landmarks is performed as described in chapter 4, and took about 60 sec. Applying the surface registration scheme, as described in Section 3.4, the average surface registration error was 0.98 mm computed in average running time of 5.6 sec. Figure 6.2 illustrates this registration.

In the second experiment, we acquired five MRI scans and eight 3D laser scans of the author and a colleague (19 available pairs). To test the algorithm robustness, the data was acquired with different facial expressions (Figure 6.3). Facial surface scans were acquired with a 3D laser scanner. The head outer surface extraction
Figure 6.2: The CT extracted upper face and head surfaces: (a) before registration, and (b) after registration.

Figure 6.3: Three common patient facial expressions: 1. worried with close eyes (a); 2. relaxed with close eyes (b), and; 3. relaxed, with open eyes (c).

from MRI images was performed as described in chapter 4, and took about 120 sec. Extraction of anatomical landmarks was performed as described in chapter 4, and took about 60 sec. Table 6.1 summarizes the results of the MRI/laser registration. Applying the surface registration scheme on 19 data pairs, as described in section 3.4, the average surface registration error was 0.99 mm (STD = 0.95 mm) computed in average running time of 2 sec. These results compare very favorably with those obtained by Marmulla et al [15]. Figure 6.4 illustrates this registration.

To visualize the results, a registration visualization software was implemented. The MRI extracted head’s outer surface and facial surface are shown before and after the
Figure 6.4: The 3D scanner face scan and head surface: (a) before registration, and (b) after registration.

Table 6.1: MRI/laser scan registration error for 19 data set pairs of two patients. Columns indicate MRI scans and patient attitude (worried or relaxed, eyes closed or open). Rows indicate laser scans, attitude (worried or relaxed, eyes closed in all cases) and distance between the laser scanner and the patient’s face. Each entry shows the mean (standard deviation) surface registration error in millimeters. The overall RMS error is 0.99 mm (std=0.95mm) computed in 2.04 secs.

registration. This is necessary to detect coarse misregistration. For example, if the registration results with scaling factor near zero, then the whole facial surface will be transformed near a specific point. If this point is near the head’s surface the RMS error will be small, while obviously this is not the right transformation.

The head outer surface extraction algorithm worked with all the seven MRI datasets, the automatic landmarks detection algorithm detected 100% of the eyes landmarks, and the automatic surface registration always converged to a small RMS error and
looked good visually. None of the algorithm’s internal parameters was modified in any of the experiments.

6.3 Summary

We conclude from our experimental results that automatic surface registration with overall RMS error of 1mm ($max = 2mm$), 95% of the time, in less than one minute, is practically feasible. Our algorithm proved accuracy, speed and robustness: the mean accuracy over all experiments was 1mm, the average speed was 62sec (to perform automatic landmarks detection, closed form and ICP), and our algorithm converged with all the input data pairs, regardless of the initial spatial difference or the dataset’s source type. It remains to be tested in-vivo in a surgical environment.
Chapter 7

Conclusion

This chapter summarizes the contribution of this thesis and suggests ideas for improvements and future work.

7.1 Summary

We have described a new system for automatic precise targeting in minimally invasive keyhole neurosurgery that aims at overcoming the limitations of the existing solutions. The system, which incorporates the miniature parallel robot MARS, has the potential to eliminate the morbidity and head immobilization requirements associated with stereotactic frames, to eliminate the line-of-sight and tracking requirements of navigation systems, and provide steady and rigid mechanical guidance without the bulk and cost of large robots. A surgical protocol, using the proposed system, was described according to a general keyhole neurosurgery scheme, and implementation technical issues were presented.

Technically, the key idea is to establish a common reference frame between the preoperative CT/MRI image and the intraoperative patient head and robot locations with an intraoperative 3D surface scan of the patient’s facial features. Once this registration has been performed, the transformation that aligns the planned and actual robot targeting guide location is computed. The robot is then automatically positioned and locked in place so that its targeting guide axis coincides with the entry point/target axis.

Registration of preoperative head images with intraoperative facial surface scans is a key problem, and essential for the success of the surgery. A unique algorithm was developed to solve this problem. The algorithm has two phases: 1) anatomical based registration that achieves rough, but fast alignment, regardless of the initial spatial difference; and 2) fine registration, which is computed with a robust ICP algorithm. The two-phase approach increases the registration accuracy, speed and robustness.

We implemented an intraoperative robot positioning module to help the surgeon place
the robot base close (within 5mm) of its planned position.

We implemented our algorithm and tested it on various datasets of different people, dataset sources and facial expressions. The algorithm proved to be accurate, fast and robust. Since the MRI images for the second experiment were acquired with a typical neurosurgery imaging protocol, the results should be considered as reliable also for a real system and setup.

We therefore conclude that that automatic surface registration with overall RMS error of $1\text{mm} \ (max = 2\text{mm})$, 95% of the time, in less then one minute, is practically feasible. This encourage us to build and test the miniature-robot keyhole neurosurgery system, as an accurate surface registration had achieved.

7.2 Future work

To build the miniature-robot keyhole neurosurgery system, two additional key problems should be solved: 1) intraoperative scan to intraoperative situation registration; and 2) robot coarse positioning module with a 3D scanner. Intraoperative scan to intraoperative situation registration can be achieved with a special registration jig, set on the robot base. Matching geometrical landmarks that extracted from the jig’s scan with landmarks of the real jig model, enables the registration calculation. When a 3D surface scanner is available, a complete prototype of the coarse positioning module, as described in chapter 5, should be implemented for the correct positioning of the robot base.

Because curvature depends on the smoothness of the surface, input surfaces are smoothed, so curvature measurements enable the anatomical landmarks detection. Currently, constant internal parameters define how to smooth the surface, according to its source type. A more general approach is to define a smoothness function on the surface and adjust surface smoothness according to its value.

The proposed vertices neighborhood grouping method, can be used for anatomical landmarks detection of other organs that can be characterized with curvatures measurements.
Bibliography


