A New Surface Registration Method as a Solution to Localization of Brain for Surgical Operations

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Abstract

NeuroGuide project focuses on demonstrating the feasibility of robotically assisted brain biopsies with the potential to enhance surgical precision, mitigate brain damage, and lower risks. This study combines registration, segmentation, manipulator control, and path generation to enable a fully assisted biopsy operation. The challenge lies in registering patient head coordinates to the robot's system. Surface registration techniques, employing the iterative closest point (ICP) algorithm, offer a less invasive alternative to marker-based registration. A Nachi MZ-07 robot manipulator is employed, facilitating accurate insertion of biopsy paths. NeuroGuide's findings are also applicable to deep brain stimulation (DBS). The project aims to transform brain biopsy procedures by minimizing damage through increased precision, potentially improving patient outcomes.

Introduction

NeuroGuide is a project that aims to demonstrate the feasibility of robotically assisted brain biopsy. This approach has the potential to increase the precision of the surgery, which could lead to less brain damage and reduced risk.

To better understand the surgery conditions, we have visited an open brain surgery and the operation was the removal of the tumor another operation we observed was a biopsy operation. StealthStation S7 was used during surgery to simulate the tool positions Figure 1.
Several neuronavigation systems have been developed over the time. One of the most common techniques is known as frameless stereotaxy in which the patient does not require to put a frame on their head. Frameless stereotaxy is a minimally invasive surgical technique that uses single markers mounted separately to the patient's head to track the position of a targeting device [1]. The targeting device is usually a pointer that is held by the surgeon. After registration, the position of the device is displayed in image data (usually MRI or CT) on the computer screen. Two technical concepts for patient-to-image registration have been developed: pair-point registration and surface-matching techniques.

Figure 1: A frameless stereotaxic system: the registration data and MRI can be observed from the screens. An IR tracking stereo camera system (on the top) follows the position of the pointing device [2].

In this project we combine registration, segmentation, manipulator control, and path generation to achieve a fully assisted biopsy operation. For segmentation, taking the right images and processing them is a detailed process and Stefan Bauer et al mentioned the lack of validation in some of the research is a challenge for planning and operation of brain surgery [4][3]. The main challenge we have faced is the registration of the patient's head coordinates to the robot's coordinate system. Various methods have been explored for point registration. However, marker-based pair-point registration techniques require the attachment of markers to the patient prior to image-data acquisition [1]. This can be inconvenient and can also expose the patient to additional radiation if the CT scan is used. Surface registration techniques use the surface geometry of the face for image-to-patient registration. This approach does not require the attachment of markers and can be less invasive for the patient. Surface registration algorithms calculate a transformation that aligns two surfaces optimally. This transformation can then be used for navigation during surgery. The iterative closest point (ICP) algorithm is the most common surface registration algorithm. It works by iteratively finding the closest points between two sets of points. Points can be taken using various tools and sensors, such as lasers, infrared (IR) sensors, and optical tracking systems (OTS). OTS is the most commonly used method in surgical operations today, but due to its cost, we have opted to use an IR sensor for our applications. However, with IR sensors we cannot track a tool in real time thus for real surgical operations OTS is more viable.

The manipulator that we use is the Nachi MZ-07 robot in which we collect data points and register them to the robot's coordinates. This allows us to insert the generated biopsy path into the robot and precisely position it.

In addition to brain biopsy, NeuroGuide could also be used for deep brain stimulation (DBS). The problem of path generation for DBS electrodes is similar to that of brain biopsy, and the path generation and optimization approach used in NeuroGuide are similar to those developed by Beriault et al. This suggests that the findings of NeuroGuide can be applied to similar fields including DBS [4].

The NeuroGuide has the potential to revolutionize the way brain biopsies are performed. By increasing the precision of the surgery, NeuroGuide could help to reduce brain damage and improve patient outcomes.

Methodology

Experimental Setup

Localization of the brain is a great challenge in surgical operations. In our solution approach, we utilized preoperative MRI data to achieve anatomical segmentation of the brain. ICP algorithms have been utilized to accomplish the localization of the brain under the assumption of a rigid body, neglecting the effects of any physical deformation of the face between the MRI acquisition and surgery. Due to the fact that the scalp and brain will go under the same transformation, we would have obtained the required transformation matrix to match the brain if we can match it for the scalp first.

Performance of the ICP algorithm against the noise and the number of points collected has been tested by adopting the algorithm written by [5]. This analysis later will give an insight about the requirements of the sensors. In total 14 test cases have been prepared with 1-, 2- and 3-mm Gaussian noise levels, with different noise axes and with different down-sampling ratios of 20, 50 and 100. The RMSE values of the new points have been evaluated as well as a new devised error metric of average 10cm error, which implies how much a 10cm line can diverge from its target under the rotational error.

Brainstorm is an open-source software working on MATLAB [6]. For this research, it has been utilized for the anatomical segmentation of the brain as well as the scalp and some other regions. The segmentation data can later be imported to MATLAB in the form of a point cloud. For the experimental use, we have first obtained the point cloud that belongs to the scalp and by converting it into a stereolithography (STL) format and 3D printing of only the facial region, we were able to obtain a rigid body which helped us to collect data points in the real world.

The 3D printed face mask was later placed near the robot and with the help of a Sharp brand (10cm - 80cm) infrared (IR) analog distance sensor attached on the end-effector; face scanning was accomplished. With the rough knowledge of the position of the face mask, we created a GCode which scans the face from some certain distance in the Z-axis. While the scanning is performed, the robot stays in a Z-axis value fixed to 200mm and X and Y positions change on a rectangular grid.

The IR sensor has been fixed on the end-effector with a tool looking down along the minus Z-axis. Later, the distance measurement was subtracted from the fixed Z-axis value (200mm in this case) to obtain the point readings from the face.

At the end, another point cloud belonging to the face mask according to the robot's coordinate frame has been generated. In the virtual point cloud whose coordinates are set that of the MRI machine, an initial transformation has been applied to roughly match its coordinates with the scanning results. This was just a coarse adjustment applied just before ICP and later improved the quality of ICP results tremendously.

Data Acquisition Protocol

A T2-weighted MRI data of 256x256x288 images with 1mm slices has been obtained from internal sources. Neuromorphometrics and Hammers brain atlases have been generated by using Brainstorm and CAT12 toolbox [6],[7]. Its critical regions including motor cortex, occipital lobe and auditory cortex have been extracted. The scalp was also generated with the number of vertices of 10000, erode factor of 0, fill holes factor of 2 and background threshold of 5.

By using an Arduino Uno, the distance values have been obtained from the IR sensor in the form of analog readings. A moving window averaging method with a window size of 100 has been utilized to collect measurements. An outlier removing algorithm was inserted to remove the measurement if its distance to the average is more than 1 standard deviation. Since the sensor is an analog one, a continuous reading with 1ms delays was able to be collected. The collected analog readings have been utilized to find the optimal curve. Curve Fitting Toolbox helped in that purpose and a power function yielded as the best fit [8].

One of Nachi's open-source example programs has been modified to accomplish the data recording task. It has been modified in a way that it can record the X and Y positions from the robot and the distance value coming from the IR sensor. One of the challenges was the asynchronous nature of serial communication between the Arduino and the computer. So, the overall system has been revised in a way that all the sensor readings were recorded if serial communication is available, and not-a-number (NaN) values were recorded if it is not available. All the readings are recorded in a specified file in the text format. Later, NaN values would be removed in a post-process step in MATLAB.

During the post-process step another data smoothing has been applied in the form of a moving window with a window size of 3. Due to the asynchrony in the serial communication, some sensor readings greatly diverge from the regular ones and a modulo of 1000 has been enough to remove them. Different scans with 1mm/s and 5mm/s were performed and at the end a total number of approximately 1000 data points were collected.

In the ICP algorithm, registration position tolerance and allowed tolerance on distant error were set to be 10^-16 separately. A *least squares nonlinear* model has been chosen as the type of optimizer.

Results & Discussion

Noise Analysis

The effect of the noise analysis was critical to estimate the performance of the ICP algorithm for upcoming tests. From the overall head scalp, the face mask is extracted in the pre-process, as seen in

Figure 2(a). A rigid body transformation (not including any shear or scale) was first applied to the head mask consisting of a rotation in the 3 main axes and translation.

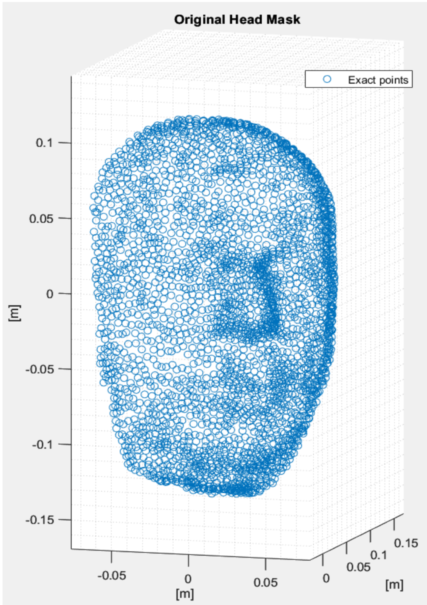
In the first test, neither noise nor down-sampling was applied to see the initial performance of the algorithm. In Figure 2(b), it can be seen that all the estimated point cloud covered all the exact points with an RMSE value of nearly zero. It further shows that the digitalization error is negligibly small, and a perfect transformation can be obtained under the conditions of a large point clouds and no noise. In Figure 2(c), the same test was repeated with 1mm Gaussian noise applied to X, Y and Z-axes separately and a down-sampling ratio of 20 was applied. Ma point cloud consisting of 3000 vertices on top of a 150 sample points yielded an RMSE of 2.8mm. In Figure 2(d), the performance of the algorithm under 1mm Gaussian noise *only* in Z-axis and a down-sampling ratio of 50 (60 points in total) can be observed. It yields an RMSE of 7.1mm. In this case, the effects of noise was limited to be only in Z-axis which would later be directly affected from the sensor measurement. Because the X and Y position coming from the internal readings of the robot, Z-axis would be the main axis struggling with the effects of noise.

The visual inspection of the noise and down-sampling confirmed that having more populous data points and less noise improves the quality of the registration. For a more detailed analysis, we ran the same test with 1-, 2-, and 3-mm Gaussian noises, again in single or multiple axes, and in different down-sampling ratios of 20, 50, and 100. The results can be further seen in Table 1. The RMSE value is a great performance metric when applied on known points.

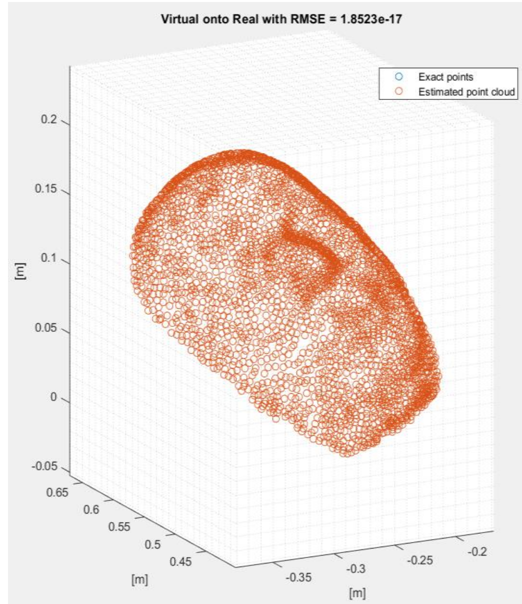
Due to the rotational estimation error while mapping the Cartesian space on another, a single point which were not included in the registration process might greatly diverge from its original position if its location is relatively far from the face. For example, if a hypothetical tumor location is far from the face, its exact location will diverge from the estimated location as it gets farther from the face. The RMSE is unable to express that kind of an error. Due to the incompetency of RMSE in that regard, a new error metric "average 10cm positioning error" has been proposed, which implies the divergence error under the rotational error for a 10cm line. The biopsy tools inserted in brain is usually about 10cm so, this kind of a definition would make a good standard. The error metric requires to be further improved, maybe under analytical solutions; however, it currently fills the lack for a rotational error metric in the literature. It is calculated according to Eqn.(1).

$$E_{10cm} = RMSE\left(\overleftrightarrow{T_{actual}} \times \overrightarrow{X}, \quad \overleftrightarrow{T_{estimated}} \times \vec{X}\right), \tag{1}$$

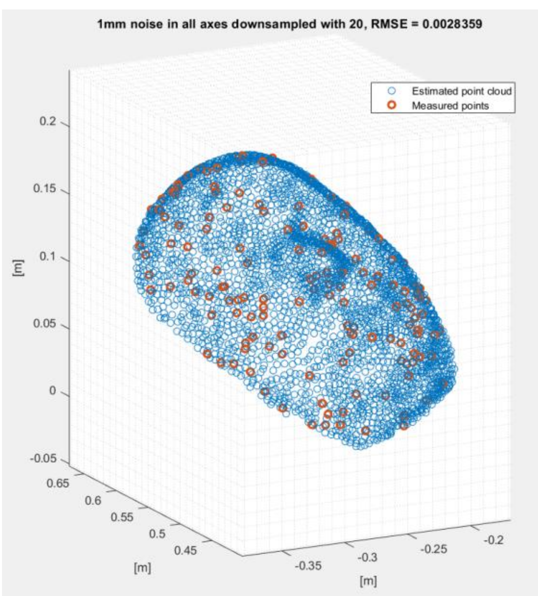
where $\overleftrightarrow{T_{actual}}$ is the real transformation between two point clouds, $\overleftrightarrow{T_{estimated}}$ is the yielding transformation by the ICP and $\vec{X}$ is a vector along the X-axis in the length of 10cm for simplicity. In the improved version, it can be calculated by using the eigenvector decomposition and the most diverging axis.



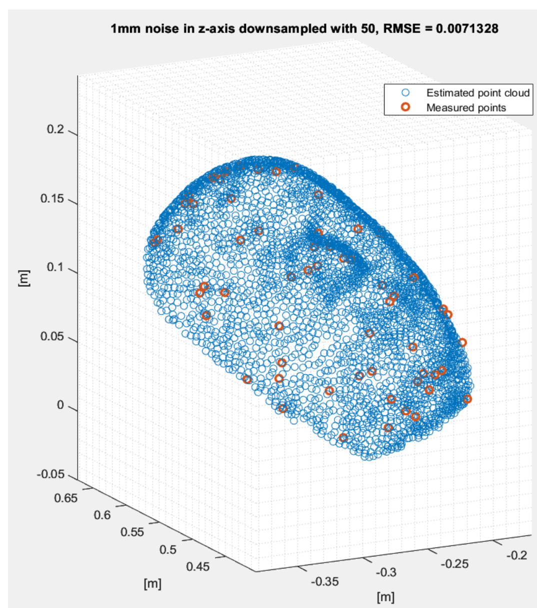
a-) Original head mask without any transformation obtained through the aforementioned data acquisition process via open-source software.



b-) Head mask under rigid body transformation without noise and without down-sampling



c-) Head mask under rigid body transformation with a Gaussian noise of 1mm in all axes and with a down-sampling ratio of 20



d-) Head mask under rigid body transformation with a Gaussian noise of 1mm ***only*** in z-axis and with a down-sampling ratio of 50

Figure 2: Some examples of rigid body registration.

Table 1: Average error for different scenarios.

Case #	Noise level (mm)	Noise axis	Down-sampling ratio	# of points	RMSE (mm)	Average positioning error in 10cm distance (mm)
1	1	Z	20	150	2.3	2
2	1	All	20	150	3	2
3	1	Z	50	60	7.1	6
4	1	All	50	60	7	6
5	1	Z	100	30	181.5	168
6	2	Z	20	150	3.2	3
7	2	All	20	150	4.8	2
8	2	Z	50	60	7.4	6
9	2	All	50	60	8.4	7
10	2	Z	100	30	181.7	169
11	3	Z	20	150	3.7	2
12	3	All	20	150	6.7	5
13	3	Z	50	60	6.8	6
14	3	All	50	60	9.1	7

From Table 1, it can be observed that the registration quality improves as the number of points collected and as the noise reduced. The effect of noise in single or multiple axes does not really matter. One of the most important findings of this analysis is that as the number of measured points increases the effect of noise becomes the secondary importance. Good registration results have been obtained for 150 measurements regardless of the noise level. On the other hand, if the collected points are too few, the algorithm cannot find the correct transformation and the error increases. All the registration experiments with 30 datapoints failed and yielded great errors in both RMSE and average positioning error.

The main reason is that the ICP algorithm basically solves an optimization problem that is full of local minima. If the point cloud is too small, the solution gets stuck in one of them although they are totally irrelevant from the actual transformation. For example, it can be that the nose getting converged on the ear, or one of the lips, or maybe the face fits upside down on the other point cloud.

All the results suggest that more the number of points collected, better the registration quality. Therefore, small error in the sensor readings can be tolerated if the collected data is large enough. It is the strategy in the further work.

The face scanning process have been completed several times and one of them can be found in Figure 3. It yielded a visually satisfying result since the nose and two eyeholes can be easily identified. We ran the ICP algorithm to map the head mask on top of the scanning data and the result seemed to be promising as the whole face showed a great fit in Figure 4. Here, there is an important step in the registration process, and it is that we applied an initial transformation to the head mask. The transformation only consists of rotation and does not include any translation. It is a rough transformation with an eyeball estimate which would later be improved by the ICP; however, it was a necessary step for ICP to work. Otherwise, the algorithm got stuck in the local minima and a proper transformation cannot be found. Furthermore, while the robot was active the IR sensor had to deal with more noise and two possible reasons can be the jerk and electromagnetic noise. The moving window averaging with size 100 significantly solved the problem and further increasing the size gives further smoothing in the data.

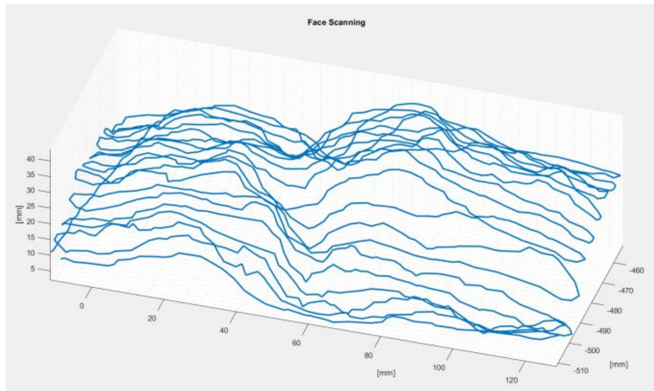
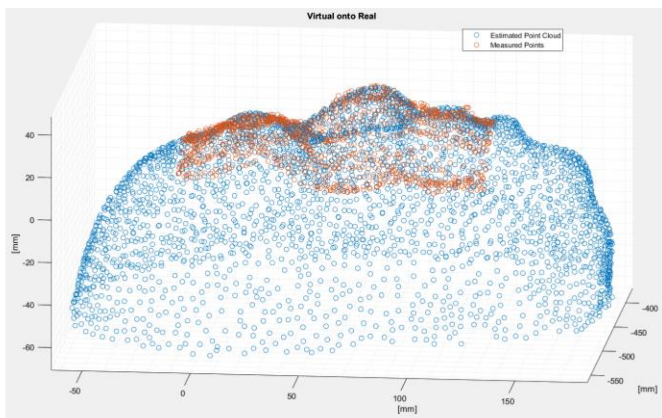
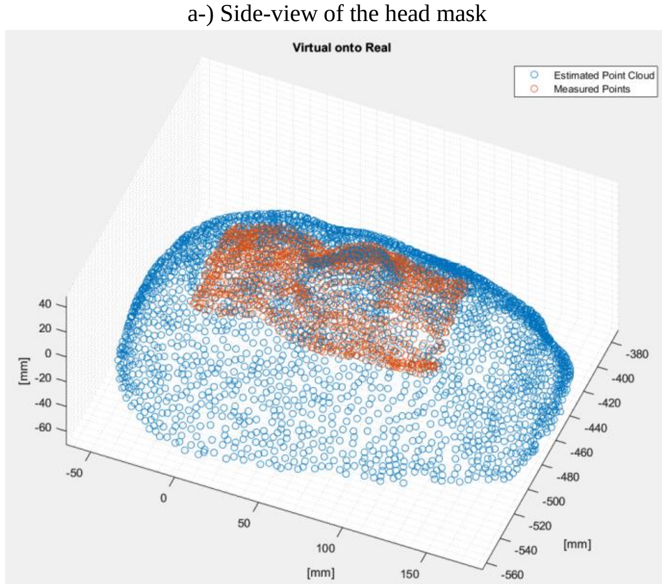


Figure 3: Face scanning results.



a-) Side-view of the head mask



b-) Oblique-view

Figure 4: Registration result.

In the further work, the quality of the registration will be tested on head mask by touching on some previously known points such as the tip of the nose or just near the eyeholes. At the end, it promises the localization of the brain and can prove itself an effective method. So far, the proposed system has two observed drawbacks: first one is that it takes approximately 20 minutes to take a complete scan from the face, and the second, it does not have any active tracking components which requires the patient to be restricted from the head during the operational procedure. On the other hand, it is a simple enough process that can be applied in a real surgical environment.

Rigid body registration and specifically ICP-based algorithms have a wide place in the literature. One of the examples is Go-ICP, which promises to solve the local minima problem that one of our serious troubles along the registration [9]. It is an open-source project and has C++ and Python code. No matter what we tried, it did not work. We have tried learning-based and feature-based models as well. However, the code repositories were too old, and we could not even compile and use some.

To deal with the local minima problem, a new algorithm was tried by implementing the cost function mentioned in [9] and using several optimization methods including *genetic algorithms* and *simulated annealing method*. However, it failed both in terms of time efficiency and local minima problem. Despite its current faults, it can have its use in the future.

Conclusion

This study's methodology tackles the challenge of brain localization in surgical procedures by leveraging preoperative MRI data for anatomical segmentation. The ICP algorithm's performance against noise and data points reveals its sensitivity. Furthermore, software tools like Brainstorm and CAT12 toolbox contributed to segmentation, while a 3D printed mask and IR distance sensor facilitated practical facial data capture. Besides, noise analysis underscored the significance of increased data points for registration quality. Initial transformations and local minima's impact on ICP emphasizes its complexities. In sum, this study presents a comprehensive approach for brain localization, offering insights into enhancing registration precision using an IR sensor and various denoising techniques. The study advances surgical navigation knowledge and enhances future brain biopsy optimization efforts.

References

[1] Eggers G, Mühling J, Marmulla R. Image-to-patient registration techniques in head surgery. Int J Oral Maxillofac Surg. 2006 Dec;35(12):1081-95. doi: 10.1016/j.ijom.2006.09.015.

[2] Medtronic. StealthStation® S7® Treatment Guidance System Manual. Dublin, Ireland: Medtronic, 2012.

[3] S. Bauer, R. Wiest, L.-P. Nolte, and M. Reyes, “A survey of MRI-based medical image analysis for Brain Tumor Studies,” Physics in Medicine and Biology, vol. 58, no. 13, 2013. doi:10.1088/0031-9155/58/13/r97

[4] S. Bériault, F. A. Subaie, D. L. Collins, A. F. Sadikot, and G. B. Pike, “A multi-modal approach to computer-assisted deep brain stimulation trajectory planning,” *International Journal of Computer Assisted Radiology and Surgery*, vol. 7, no. 5, pp. 687–704, 2012. doi:10.1007/s11548-012-0768-4

[5] Dirk-Jan Kroon (2023). Finite Iterative Closest Point (https://www.mathworks.com/matlabcentral/fileexchange/24301-finite-iterative-closest-point), MATLAB Central File Exchange. Retrieved August 21, 2023.

[6] Tadel F, Baillet S, Mosher JC, Pantazis D, Leahy RM (2011), Brainstorm: A User-Friendly Application for MEG/EEG Analysis, Computational Intelligence and Neuroscience, vol. 2011, ID 879716

[7] CAT – A Computational Anatomy Toolbox for the Analysis of Structural MRI Data, Christian Gaser, Robert Dahnke, Paul M Thompson, Florian Kurth, Eileen Luders, Alzheimer's Disease Neuroimaging Initiative, bioRxiv 2022.06.11.495736; doi: https://doi.org/10.1101/2022.06.11.495736

[8] MathWorks. Curve Fitting Toolbox. Natick, Massachusetts, United States: MathWorks, 2020.

[9] J. Yang, H. Li, D. Campbell, Y. Jia, Go-ICP: A Globally Optimal Solution to 3D ICP Point-Set Registration, IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 2016.