Evaluation of CT Registration for Image-Based Sinus Reconstruction

Team 12

Project Proposal

Computer Integrated Surgery II

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Mentors:

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Introduction

I. Clinical Motivation

Nasal obstructions are a common clinical problem that can significantly impact patients' quality of life. Septoplasty and turbinate reduction are two of the most common surgical interventions used to address this problem which are shown in Figure 1.

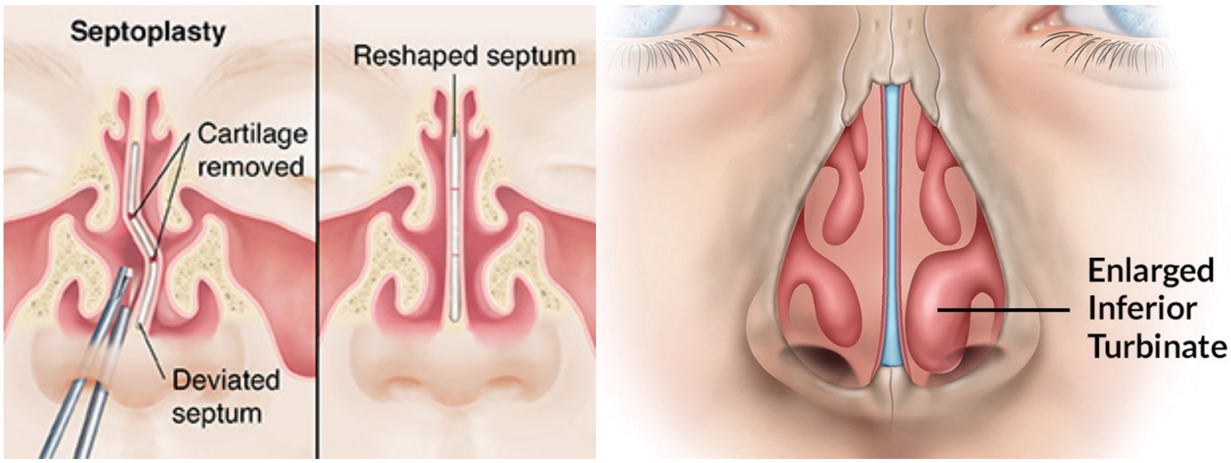

Figure 1. Example patient conditions that may cause nasal obstructions. (a) Anatomical diagram from [1] *of deviated septum which may suggest septoplasty surgery is needed to reshape the anatomy. (b) Anatomical diagram from* [2] *of enlarged turbinate in the sinus cavity that may motivate turbinate reduction surgery.*

Clinical studies have provided evidence towards positive impact of these interventions in patients' quality of life [3, 4]. However, these assessments rely on subjective measures such as patient-reported symptoms and there is limited quantitative evidence to support the effectiveness of these surgeries [5]. This creates a need for objective evaluation methods to inform clinicians about which patients are most likely to benefit from surgical intervention and provide tools for longitudinal assessment of the surgical outcomes.

Quantitative evaluation of the patient sinus anatomy requires geometric information of the nasal cavity. Computed tomography (CT) scans provide this information, however, these scans are expensive and expose patients to harmful radiation. This motivates an image-centered approach that leverages routine endoscopy procedures that physicians use to examine patients. An accurate 3D model of the sinus anatomy is required to retrieve clinically relevant parameters, such as aperture and volume, which can be used for quantitative assessment of patient anatomy.

II. Prior Work

Liu et. al [6] developed a pipeline to generate a dense 3D reconstruction of the sinus anatomy from endoscopic video as shown in Figure 2.

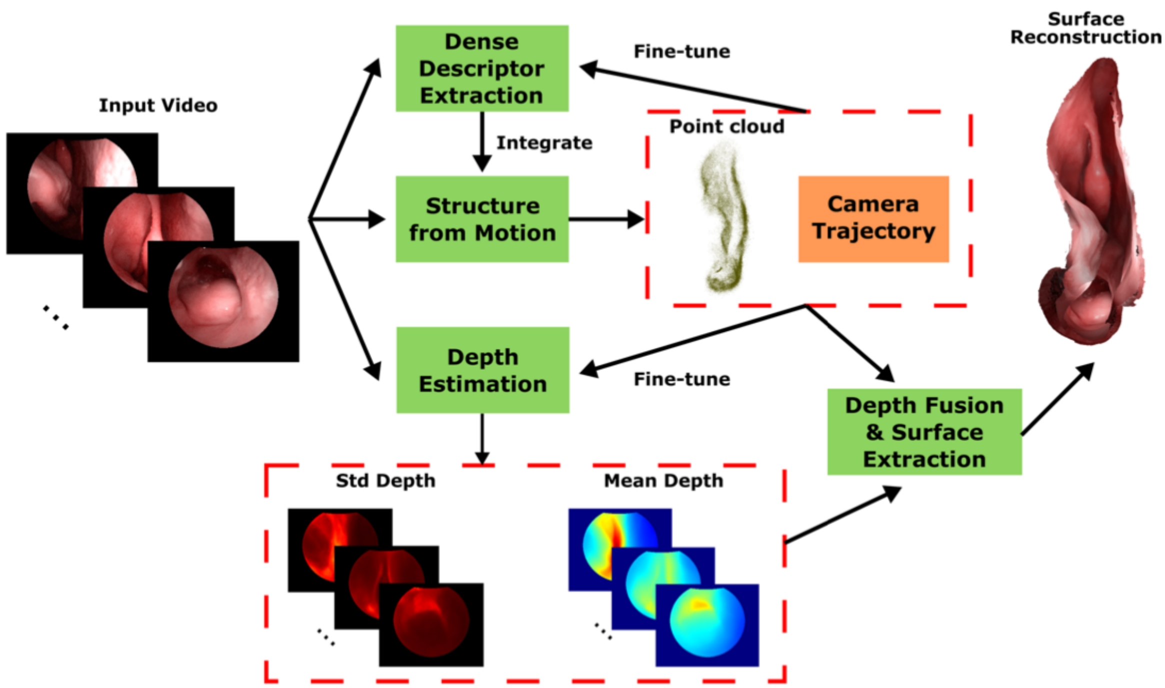

Figure 2. Dense reconstruction pipeline adapted from [6].

The pipeline utilizes a Structure from Motion (SfM) algorithm [7] which matches common visible points in input images to produce a 3D structure of the object in the image. The visible points are matched using dense feature descriptors which are extracted using a deep learning model. These dense descriptors are then integrated into SfM to produce a dense point cloud of the anatomy and the camera trajectory for each frame in the input sequence.

The input sequence is also used to estimate the depth of the images from the camera using a deep learning model [8]. The depth estimation, point cloud, and camera trajectories are then used in a depth fusion method to produce a 3D reconstruction of the sinus cavity. Currently, there is no assessment framework towards the correctness of the image-based 3D reconstruction.

III. Goals

The main goal of this project is to implement a quantitative framework to evaluate the accuracy of the dense reconstruction based on the ground truth CT. The development of this assessment and framework would enable further research towards the usage of the sinus reconstruction pipeline in clinical settings. The specific aims of this project are listed as follows:

1. (Minimum) Implement a rigid registration framework to evaluate the image-based 3D reconstruction of the sinus anatomy with respect to the corresponding CT image.
    a. Evaluate global registration considering entire reconstruction.
    b. Evaluate local registration of specific anatomical regions of interest in the reconstruction.
    c. Implement methods to report evaluation metrics and visualizations to allow for both quantitative and qualitative assessment of the registration.
2. (Expected) Analyze the influence of uncertainty in the reconstruction pipeline, and evaluate the resulting reconstruction with respect to the CT.
    a. Analyze the distribution of uncertainties in depth estimation for features present in multiple input image sequences.
    b. Integrate probabilistic model to adjust the influence of estimations based on analysis of uncertainty distribution.
3. (Maximum) Integrate robot kinematics in the registration process and evaluate results with respect to the CT.

Technical Summary

This project requires input data of endoscopic video sequences and CT scans of the same sinus anatomy. The data utilized for the maximum goal requires sequences obtained using the Galen robot to retrieve corresponding robot kinematics at the time of video capture. The endoscopic sequence for the dense reconstruction pipeline and the resulting 3D structure will be used for the registration with the corresponding CT scan to report an accuracy evaluation.

The input data must be pre-processed for use in this project. The endoscopic video and robot kinematics are collected using a Robot Operating System based platform and need to be extracted to use as input in the dense reconstruction pipeline. The image frames of the video sequence will be used in the pipeline to generate the 3D reconstruction. The CT scans will also need to be segmented using 3D slicer [9]. The 3D reconstruction and segmented CT will then be used towards the rigid registration.

The general approach is to first implement the registration framework and evaluation methods, analyze uncertainties in the dense reconstruction, and finally integrate robot kinematics in the registration. The proposed workflow of the project is shown in Figure 3.

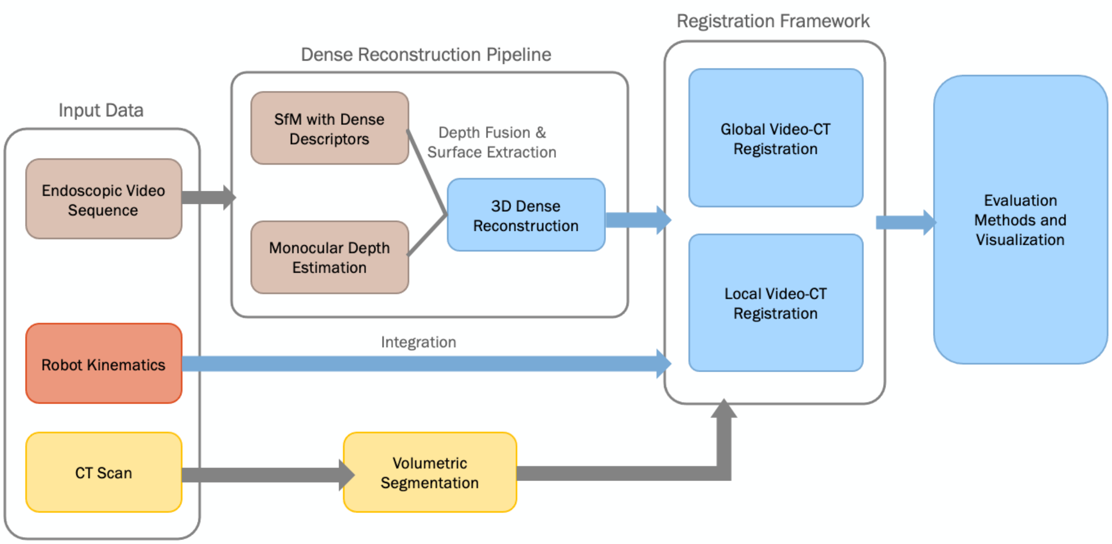

Figure 3. Proposed workflow of planned modifications and implementations shown in blue.

I. Registration Framework

I plan to integrate rigid registration methods including the iterative closest point (ICP) algorithm and iterative most likely point algorithm [10] to register the dense reconstruction to the corresponding CT image. The iterative most likely point algorithm and variations will be integrated using the cisstICP library available on GitHub [11]. These methods will be used to perform both local and global registrations. At the global scale, the entire reconstruction will be used for the registration. In order to perform local registration, I plan to implement methods to isolate specific anatomical regions of interest in the reconstruction by isolating a subset of frames from the input video sequence to reconstruct only a portion of the sinus anatomy. The resulting reconstruction will then be used to apply local registration to the CT.

Additionally, I plan to develop methods to report evaluation metrics and visualizations for both quantitative and qualitative assessment of the registration. This will include a summary of the error magnitude between projected points of the reconstruction to the ground truth CT points and an overlay of the registered reconstruction and CT. I plan to include visual differences of the points in the overlay to allow for clearer comparison of the variation in error magnitude. This framework will allow me to produce a baseline evaluation of the accuracy of the 3D sinus reconstruction to use as a point of comparison for subsequent changes.

II. Influence of Uncertainties in Dense Reconstruction Pipeline

The dense reconstruction pipeline utilizes depth estimations in addition the SfM point cloud and camera trajectories to generate the 3D structure. This information is integrated into a fusion method which resolves variation between the estimates of common points in multiple frames of the input sequence [12]. The fusion method currently considers every estimate equally; however, the points in the sinus anatomy that are further away from the camera when the image is captured is shown to have more uncertainty as seen in Figure 4.

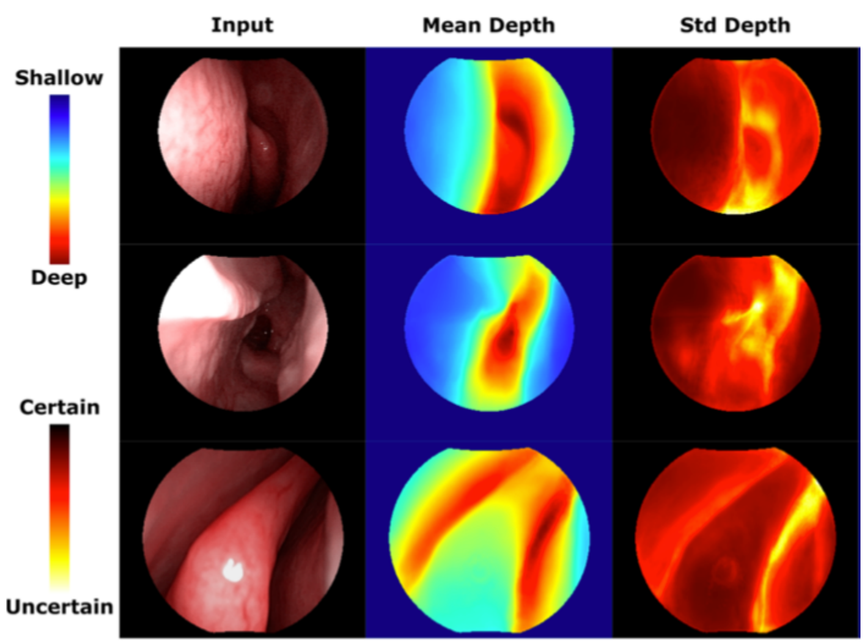

Figure 4. Adapted from [8]. *Heat map of mean and standard deviation of depth estimates with corresponding input image. The deeper mean depth estimation, meaning further away from the camera at capture, exhibits higher uncertainty.*

We hypothesize that this uncertainty may be introducing errors which are propagated into the reconstruction. I plan to analyze these uncertainties by examining the depth estimations for features that contribute to the same point in the point cloud to evaluate the distribution of the uncertainty. Based on this analysis, I will then integrate a probabilistic model in the pipeline to account for these uncertainties and limit the influence of inaccurate depth estimations to generate new reconstructions. The effectiveness of this adjustment will then be evaluated using the registration framework.

III. Integration of Robot Kinematics

Robot kinematic data has been collected which corresponds to the endoscopic video sequences and CT scans. This data provides information related to the location of the endoscope camera. The SfM in the current reconstruction pipeline produces camera trajectories which is used as input to the depth fusion and surface extraction to produce the 3D structure. I plan to further analyze this step in the pipeline to develop a stronger understanding of the current implementation using the camera trajectory input. I will then work towards integrating the additional robot kinematic data to fine-tune the SfM trajectories. This integration will produce another reconstruction which will also be evaluated using the rigid registration methods.

Dependencies and Deliverables

I. Dependencies

This project requires various dependencies described in Table 1. This includes software for the dense reconstruction pipeline [6], cisstICP library [11], and 3D slicer [9] which have all been installed. Computing power is also required to generate the dense reconstructions of the sinus anatomy. Additionally, the deliverables of this project require input data including the endoscopic video of the sinus and corresponding CT scans and robot kinematics. All the dependencies have been resolved.

Table 1. Summary of dependencies with associated need and contingency plans.

Dependency	Need	Status	Follow-up	Contingency Plan
Computing Power	Run dense reco pipeline	Ready to use	ARCADE lab workstation	N/A
Dense Reconstruction Pipeline	Generate 3D sinus reconstructions	Ready to use	N/A	Available on github
cisstICP Library	Implementation of registration methods	Installed	N/A	Available on github
3D Slicer	Segment CT scans	Installed	N/A	N/A
Sinus Data	Input for dense reconstruction pipeline	Available	N/A	Additional cadaveric data collection sessions
CT scans	Ground truth	Available	N/A	Additional cadaveric data collection sessions
Robot kinematic data	Integration into reconstruction pipeline	Available	N/A	Additional cadaveric data collection sessions

II. Key Activities and Deliverables

The main activities and associated deliverables for this project are described in Table 2. The minimum goal of registration framework will result in code and documentation as well as a baseline report of the evaluated data. The expected and maximum goals will also produce code and documentation towards the changes made to generate a new dense reconstruction and perform the registration to report the comparison with the baseline.

Table 2. Summary of planned activities and corresponding deliverables.

	Activities	Deliverables
Minimum	Data pre-processing: generate dense reconstructions and perform CT segmentation	3D Dense Reconstruction and Segmented CT scans
	Integrate rigid registration methods (ICP, IMLP and variations) for global registration	Code and documentation
	Implement data processing steps to isolate local regions and apply rigid registration methods	Code and documentation
	Report error evaluation between dense reco and CT ground truth with visualizations	Report of evaluated data
Expected	Adjust depth fusion step in pipeline to account for uncertainties in estimation	Code and documentation
	Evaluation of new dense reconstruction	Resulting dense reconstruction and comparison report
Maximum	Integrate robot kinematics into registration method	Code and documentation
	Evaluation of new dense reconstruction	Resulting dense reconstruction and comparison report

III. Timeline

The activity timeline for this project is broken into five main tasks based on setup, minimum, expected, and maximum goals, and final report writing as shown in Figure 5. Initial setup and data pre-processing will be done first to integrate the necessary software and produce input data for the registration framework. The minimum goal of implementing the registration framework is expected the week of March 13, 2023, expected goals are expected by the week of April 10, 2023, and the maximum goal by May 1, 2023. Achievement and completion of these goals and activities will be documented by the previously described deliverables.

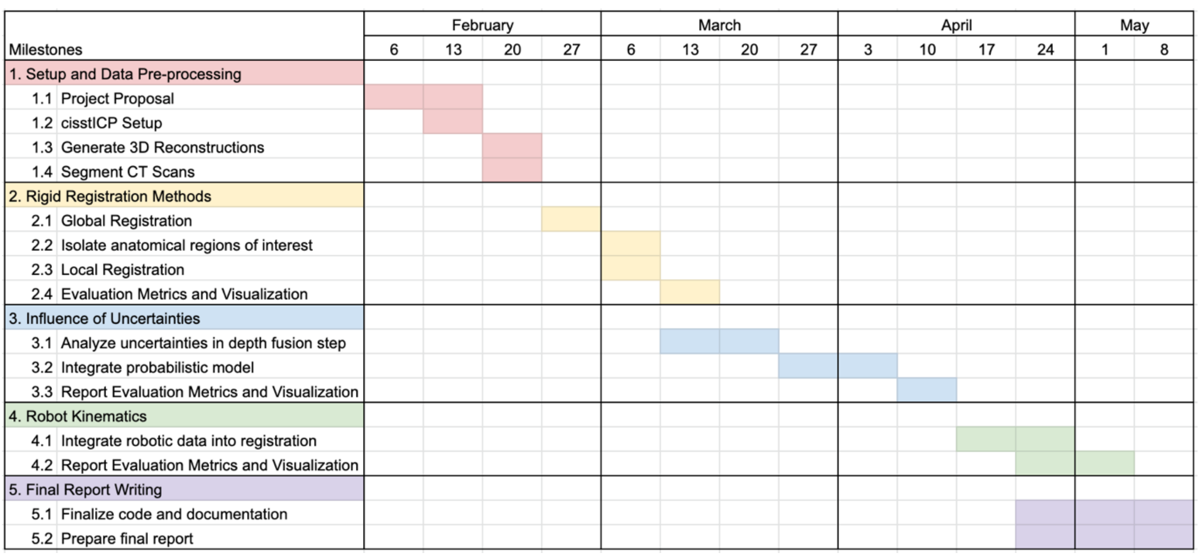

Figure 5. Project Timeline.

Management Plan

I. Team Members and Roles

Jan Mangulabnan
PhD Student in Computer Science, ARCADE Lab
Responsible for all tasks required for this project.

Timo Teufel
Visiting Student in ARCADE Lab
Assist with data pre-processing and generating dense reconstructions.

Dr. Roger Soberanis
Postdoc in ARCADE Lab
Primary mentor who will serve as the main point of contact for concerns and provide expertise on the dense reconstruction pipeline.

Dr. Mathias Unberath
Assistant Professor in Computer Science, Principal Investigator of ARCADE Lab
Mentor who will provide additional expertise on the dense reconstruction pipeline and help ensure project direction aligns with overall research goals.

II. Meetings

I work daily with Dr. Roger Soberanis, in our shared workspace, Hackerman B05. As we are in constant contact, we do not believe it is necessary to schedule a weekly meeting as he is generally available to help address concerns regarding this project. If larger complications arise, we may formally schedule a meeting to discuss in greater detail. Additional meetings are scheduled to maintain accountability and manage the timeline as follows:

Weekly Thursday 4:15pm – 5:15pm: ARCADE lab meetings for general progress updates.

Bi-Weekly Tuesday 12:00pm – 12:30pm: One-on-one meetings with Dr. Mathias Unberath to address specific concerns and report detailed progress.

III. Platforms

Communication: Majority of communication will occur in-person in Hackerman B05. Additional communication will occur via Slack.

Code: Code and documentation will be maintained on a private repository on GitHub.

Data: The input data will be maintained on an existing 12 TB hard drive located in Hackerman B05 used solely for sinus project-related file storage.

Reading List

X. Liu *et al.*, "Reconstructing sinus anatomy from endoscopic video–towards a radiation-free approach for quantitative longitudinal assessment," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2020: 23rd International Conference, Lima, Peru, October 4–8, 2020, Proceedings, Part III 23*, 2020: Springer, pp. 3-13.

X. Liu *et al.*, "Dense depth estimation in monocular endoscopy with self-supervised learning methods," *IEEE transactions on medical imaging,* vol. 39, no. 5, pp. 1438-1447, 2019.

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[11] A. Sinha, "cisstICP Library," ed. https://github.com/AyushiSinha/cisstICP: GitHub, 2019.

[12] B. Curless and M. Levoy, "A volumetric method for building complex models from range images," in *Proceedings of the 23rd annual conference on Computer graphics and interactive techniques*, 1996, pp. 303-312.