Project Plan Proposal

Cross Modality Medical Image Synthesis and Registration through Machine Learning

600.456/656 Computer Integrated Surgery II

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Contents

1 Background and Motivation

Magnetic Resonance Imaging (MRI) is a commonly used imaging technology for the diagnosis of the hip osteonecrosis, which is a disease resulting in the death of bone cells. Core decompression is a commonly used surgical method for the removal of the ostenecrotic tissue (dead bone) from the femoral head.

In order to remove necrotic tissue in the femoral head, surgeons rely on preoperative MR scans for tool trajectory planning and take intraoperative X-ray shots to monitor the procedure. However, there are currently no simple method that could easily translate the tool trajectories annotated on the MR scans to the intraoperative X-ray shots. Thus, the aim of this work is to propose machine learning based algorithms that registers the paths between the two image modalities.

Figure 1: Illustration of the annotated drilling path in both MRI (left) and X-ray (right) during core decompression surgery [1]

2 Project Goals and Significance

The goal of this project is to create a workflow that allows this registration process to be achieved. In this work, this goal is approached by the following two-step registration process.

- Synthesization of computerized tomography (CT) images given MR images as inputs
- Registration between synthesized CT images and target X-ray images

The algorithms developed for the two steps will be tested and evaluated using the AVN Dataset, which consists of medical images of different image modalities from 30 patients.

The currently available MR to X-ray registration algorithms are mostly intensity- or feature-based methods, which are likely to work well on specific datasets and may not produce satisfactory results when applied to images focusing on another body part. This project provides a learning-based solution for the registration task. If the proposed method is successfully developed, it would be a more flexible approach that could work well on most datasets compared to existing methods as most model parameters would be learned during the training process.

3 Technichal Approach

3.1 Synthesize CT images from MR images

A cycle-consistent adversarial networks (CycleGAN) [2] is an unsupervised image-to-image translation network. Unlike other image translation network architectures which require paired images as the training dataset, CycleGANs learn from unpaired images and perform image translation in the absence of paired examples.

The AVN dataset available consists of medical images of the hips from 30 patients, including CT scans from 11 patients, MR scans from 19 patients, and X-ray images from 21 patients. Since not all three modalities of the hip are available for all patients, we have identified that CycleGAN is a valid approach to translate MR to CT images.

Fig.2 below illustrates the cycleGAN network architecture that would be developed in the project. Using the unpaired CT images ($\mathcal{I}_{CT}$) and MR images ($\mathcal{I}_{MR}$) from our datasets, four models would be trained, including the generator the generator that synthesizes CT images from given MR images (G_{CT}), the generator that synthesizes MR images from CT (G_{MR}), the discriminator of CT images (D_{CT}), and the discriminator of CT images (D_{MR}).

The goal for this step is to produce a reliable MR to CT generator (G_{CT}) that could successfully generate realistic CT images from MR images as shown in Fig.3.

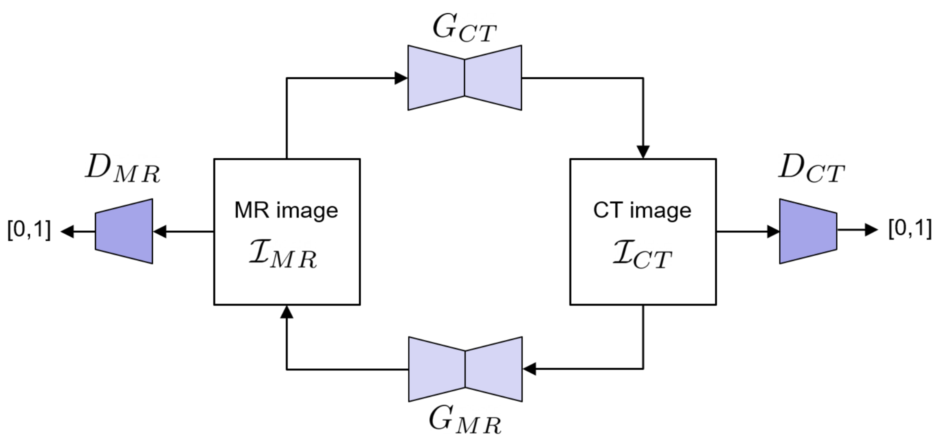

Figure 2: CycleGAN network overview

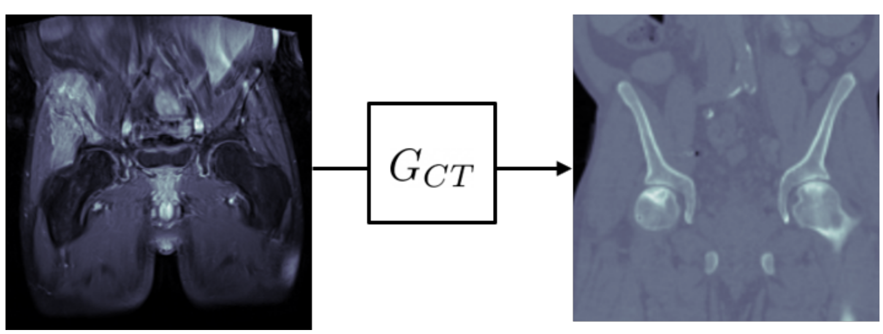

Figure 3: Illustration of the generator G_{CT} from the CycleGAN network

3.2 Registration between CT and X-ray (2D/3D Registration)

The second step of our workflow is considered as a 2D/3D registration process. In a 2D/3D registration problem, the objective is to find a rigid pose of 3D data so that it aligns with the target 2D image. Once the 3D CT images are generated from the CycleGAN network, we will then perform 2D/3D registration between the synthesized CT and our target X-ray image.

One of the most common approaches to perform 2D/3D registration is through the production of digitally reconstructed radiographs (DRRs) from CT images through ray-casting [3]. Since the DRR generation process simulates the X-ray capturing process, the registration task could be formulated as an optimization problem that attempts to find the ideal rigid CT poses (θ) that produce DRRs with the highest closeness to the target X-ray image as shown in the equation below:

$$\min_{\theta} \quad \lambda \cdot S(P(\theta), I) + (1-\lambda) \cdot R(\theta)$$

S: Normalized cross correlation	R: regularization function	θ: CT bone poses
P(θ): Generated DRR given θ	I: target x-ray image	λ: regularization parameter

In this work, the optimization-based approach will be performed to tackle the 2D/3D registration between the synthesized CT and the X-rays. Methods such as multi-start strategies [4] could be implemented for better initial pose estimation to prevent the optimization process being trapped in local optima.

4 Dependencies

The dependencies of this project are shown in Fig.4 below, with the plans and the estimated resolving time. Alternative plans are proposed for each dependency to mitigate the risk of original plans failing. Current status has also been shown in the table and will be updated frequently on ciis wiki page.

Dependency	Plan	Estimated time	Status
GPU resource access for network training	Talk to Dr. Armand to get access to MARCC	2/26	Request for MARCC allocation submitted on 2/23, waiting for the response
	(alternative) Lab GPU resource (thin6), Google cloud	Resolved	Access to thin6 has been acquired.
Access to CT dataset for additional training images	Request access to New Mexico Database	2/26	Access to images of 24 additional patients submitted on 2/22, waiting for response
	(alternative) Raise the issue during the 3/2 weekly meeting with Dr. Armand.	3/2	
Acquire tool path annotations in MR images	Check with Alejandro if we can get collect annotated MRs from surgeons	3/18	I will be discussing this during my 3/1 meeting with Alejandro
	(alternative) Generate simulated tool paths ourselves	3/20	I have access to Imfusion Suite which allows simple path annotations to be made (two points that forms a line). The method to extract the paths out from the software still needs to be figured out.

Figure 4: Project dependencies

5 Project Timeline

The project timeline for the project mainly consists of three parts: (1) MR to CT synthesis, (2) 2D/3D registration, and (3) Code optimization. The timeline is presented as a Gantt chart shown in Fig.5 below.

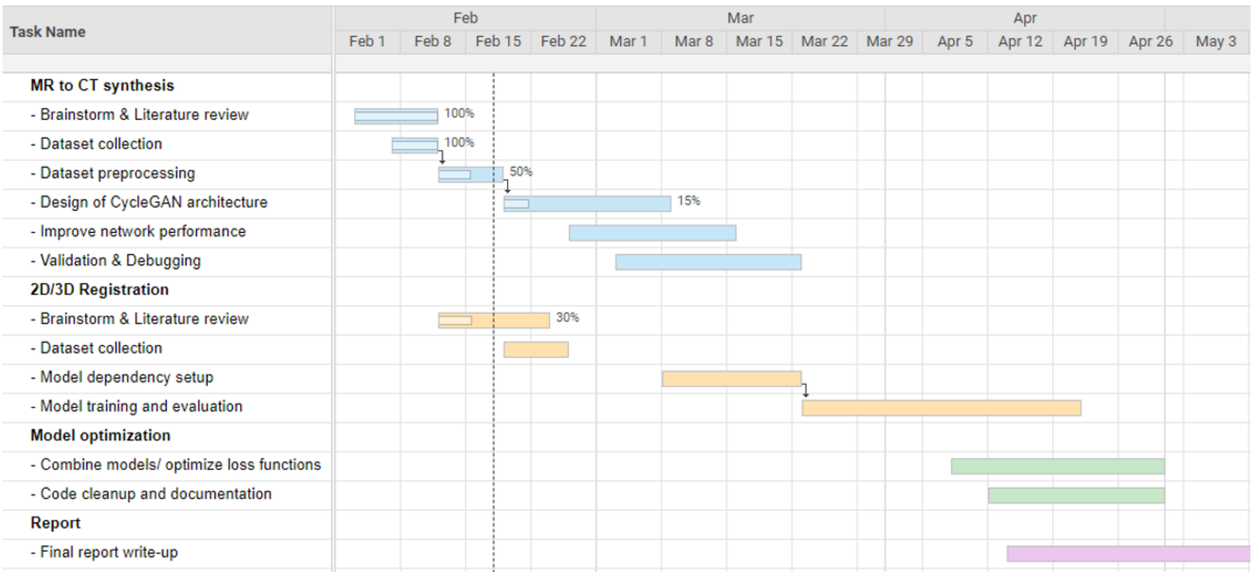

Figure 5: Project timeline Gantt chart

6 Milestones

The project milestones are listed below. The status of each milestone will be updated frequently on the ciis wiki page.

- MR to CT synthesis - Dataset collection (Planned Date: 2/15)
- MR to CT synthesis - MR to CT synthesis - Dataset preprocessing (Planned Date: 2/18)
- MR to CT synthesis - CycleGAN network architecture design (Planned Date: 3/08)
- MR to CT synthesis - Network performance improvement (Planned Date: 3/15)
- MR to CT synthesis - Validation and debugging (Planned Date: 3/21)
- CT to X-ray registration - Model dependency setup (Planned Date: 3/21)
- CT to X-ray registration - Model training and evaluation (Planned Date: 4/18)
- Code optimization - Combination of model loss (Planned Date: 4/29)
- Code optimization - Code cleanup and documentation (Planned Date: 4/29)
- Final report write-up and presentation (Planned Date: 5/06)

7 Roles and Responsibilities

7.1 Team Members

- Ku Ping-Cheng (pku1@jh.edu): Takes the responsibility for all tasks in this project

7.2 Mentors

- Dr. Alejandro Martin Gomez (alejandro.martin@jhu.edu)
- Dr. Mehran Armand (Mehran.Armand@jhuapl.edu)

8 Management Plans

8.1 Meetings

Currently I am meeting weekly with both of my mentors. The first meeting is with Dr. Alejandro at Monday 3:30PM and the second is with Dr. Armand at Tuesday 3PM.

8.2 Software

All code written for this project will be stored locally while under development. A private repository will be created on Github for backup. The repository would be published after documentation is complete.

9 Reading List

- Yi, X., Walia, E., Babyn, P. (2019). Generative adversarial network in medical imaging: A review. Medical Image Analysis, 58, 101552. doi:10.1016/j.media.2019.101552
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- Yi, X., Walia, E.; Babyn, P. (2019). Generative adversarial network in medical imaging: A review. Medical Image Analysis, 58, 101552. doi:10.1016/j.media.2019.101552

References

[1] *Osteonecrosis of the Hip - OrthoInfo - AAOS*. URL: https://orthoinfo.aaos.org/en/diseases--conditions/osteonecrosis-of-the-hip.

[2] Jun-Yan Zhu et al. “Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks”. In: *2017 IEEE International Conference on Computer Vision (ICCV)* (2017). DOI: 10.1109/iccv.2017.244.

[3] George W. Sherouse, Kevin Novins, and Edward L. Chaney. “Computation of digitally reconstructed radiographs for use in radiotherapy treatment design”. In: *International Journal of Radiation Oncology*Biology*Physics* 18.3 (1990), pp. 651–658. DOI: 10.1016/0360-3016(90)90074-t.

[4] Yoshito Otake et al. “Robust 3D–2D image registration: application to spine interventions and vertebral labeling in the presence of anatomical deformation”. In: *Physics in Medicine and Biology* 58.23 (2013), pp. 8535–8553. DOI: 10.1088/0031-9155/58/23/8535.