Automatic Segmentation of Anatomical Structures for Core Decompression Procedures

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1. Introduction, Topics and Relevance

Osteonecrosis of the femoral head (ONFH) refers to the disease that bone cells in the hip joint are dead due to insufficient blood supply to the femoral head. It could lead to failure of the subchondral bone [11]. ONFH affects especially young adults aged between 30 to 50, and the incidence rate of ONFH keeps increasing [10].

Core decompression is a common treatment to both prevent or delay the worsening of early-stage ONFH or as a step of Total Hip Arthroplasty (THA) surgery when ONFH develops to subchondral bone collapse [4]. For the core decompression process, MRI shows a great advantage in pre-operative imaging and surgical planning due to its sensitivity to necrosis, but it's in short of imaging bones. Intraoperatively, only CT is applicable. On the contrary to MRI, CT shows more advantage on imaging bones; however, necrosis tissue is hard to distinguish.

A promising method to exploit the strengths of these two medical image technologies is to register MRI and CT volume. With appropriate registration, the surgical planning performed on the MRI imaging can be mapped to the CT volume. However, to accurately register the volumes, precise segmentation of CT and MRI are firstly expected. This is specifically hard for MRI due to its insensitivity to bone anatomy and lower contrast. Currently, the segmentation of MRI is done manually by expertise, which normally takes up to hours of work.

In this work, benefiting from the development of deep learning in medical image processing, the automatic segmentation of MRI volume of core decompression related anatomic structures is to be achieved. With the previous work on CT segmentation and 3D-3D registration, automatic and end-to-end segmentation of MRI and CT volumes for core decompression procedures, followed by the registration between the segments, is to be developed.

2. Objectives

2.1. Project Goal

- Realize the automatic segmentation of the anatomical structures, including femur, pelvis, and necrosis, in MRI volumes used for core decompression procedures.
- Realize the automatic segmentation of femur and pelvis in CT volumes used for core decompression procedure.
- Realize the registration between the segmented anatomical structures (femur and pelvis) in MRI (first goal) and CT (second goal). A further topic is integrating the segmentation and registration models to form an integrated system and realize its interaction with 3D Slicer.

2.2. Deliverable

The detailed objectives are shown as:

- Minimum:
  - Develop a model that automatically segments the femur, pelvis, and necrotic tissue from MRI for core decompression procedure.
  - Code management and project documentation.
- Expected:
  - By accomplishing the minimum objective, develop models to automatically segment the femur and pelvis from CT for the core decompression procedure.
  - Use the MRI and CT segments, realize the manual registration between MRI and CT.
- Maximum:
  - Interact the segmentation and registration pipeline with 3D Slicer.
  - By accomplishing the expected objective, automatically register the femur and pelvis (MRI - CT).

3. Summary of Approach and Related Work

3.1. Data set

The data set contains MRI-CT volume pairs of ONFH patients; 19 pairs have been obtained currently. The MRI data will be annotated using 3D Slicer [12] and used for supervised learning.

3.2. Method on MRI segmentation

U-Net [13] shows great success on pixel-level segmentation in the medical field. Denix et al. [5] used the U-Net and its 3D extension for a binary segment of the proximal femur in MRI volume. Later, Isensee et al. [6] proposed a self-configured segmentation model based on U-Net and tested it on segmentation tasks with multi-objects.

In this project, the segmentation of MRI volume is firstly realized based on the baseline model — the nnU-Net [6]. nnU-Net is desired to provide an appropriate segmentation model for the rest of the work in this project. By accomplishing the baseline training, more work will be dedicated to improving the performance of MRI segmentation using 3D CNN models, from the perspectives that:

- Loss function: improve the loss function with combinations of Hausdorff distance, dice loss, and negative log-probability.
- Dilation rates: empirically, appropriate dilation rates could improve the model's performance [5].
- Encoder: More advanced visual encoder, for instance, vision transformer [8], could improve the model's performance.

3.3. Method on CT Segmentation

Contributive studies have been dedicated to CT volume segmentation. The conventional threshold-based method is shown to work on CT femur segmentation. Zoroofi [14] introduced an automatic segmentation pipeline based on prepossessing, histogram-based thresholds, and post-processing. Krčah et al. [9]adapted the Graph-cut framework onto automatic femur bone segmentation and could perform without giving prior data on the model. Segmentation on CT volume can also be well handled using a learning-based method. Bjornsson [3] used a 3D CNN based on U-Net to realize the automatic segmentation of femur CT volume.

In this project, the threshold-based algorithm, for instance, the work of Zoroofi [14], is firstly considered, which will serve as a baseline model. The improved model, if necessary, is planned to be another 3D CNN model. The threshold-based segmentation results (with appropriate manual corrections if needed) will then be used as the ground truth annotations for the improved models. Theoretically, the 3D CNN model for CT segmentation can be modified on the basis of the MRI segmentation model.

3.4. Method on MRI-CT registration

The registration can be done either manually or automatically. Trained expertise could manually align the images, or semi-automatically, select landmarks on both MRI and CT and use algorithms including ICP [2] to solve the registration. Automatically, well-developed 3D to 3D registration algorithms have been applied to medical image registrations. Conventional algorithms have been well integrated into registration tool kits. For example, ANTs [1] is developed to use Symmetric Normalization to find the mapping of deformable and affine transformations. Elastix [7] introduces parametric approach for solving non-rigid registration. The learning-based method is also studied to solve registration problems.

In this project, the manual registration based on segments from MRI and CT will firstly be realized. The segments will be outputted as a segmentation file that 3D Slicer [12] could read. The alignment of segments, as well as the selection of landmarks, will be done manually through the interface.

One step further, the semi-automatic registration is planned to be realized using Symmetric Normalization from ANTs [1]. Using the MRI and CT volume segments (and the initial transformation from manual step), the registration algorithm will then compute the transformation between MRI and CT. Finally, the two segmentation models and the registration model will be integrated together to form an end-to-end system and, if possible, to be integrated with 3D Slicer software.

4. Timeline

See appendix for the Gantt Chart.

5. Responsibilities

The project is assigned as an individual project to Mingxu Liu, and he will be fully responsible for all work in this project except the necessary assistance from mentors, including support of GPU servers, advising and problem-solving, etc.

6. Dependencies

Dependencies	Date	**Status**	Alternatives / Solution	Significance
Access to ONFH data	2/17	Acquired	NONE	Essential, cannot work without the access
Access to GPU server	3/2	Acquired	Commercial GPU Server (Google Colab / AWS)	Still performable on Alternatives with additional cost
Managed to interact with 3D Slicer	4/14	In Progress	Build the module and use temporary I/O for system testing	Does not affect the progress of the expected deliverables, but may need to finalize the work after the course

Fig. 1. Project Dependencies.

7. Management Plan

- Weekly Meeting with mentors on Wednesday.
- Communication via email and Lab channel.
- All contents, including literature, data set, code, and other relevant materials stored in project One Drive.
- Code Management on GitHub repository, and regular backup on project One Drive.
- The documentation and code management will be throughout the entire project.

8. Reading List

Most relevant related work is listed as: [11], [5], [13], [9], [14], [3], [1]. Other related papers can be found in reference.

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9. Appendix

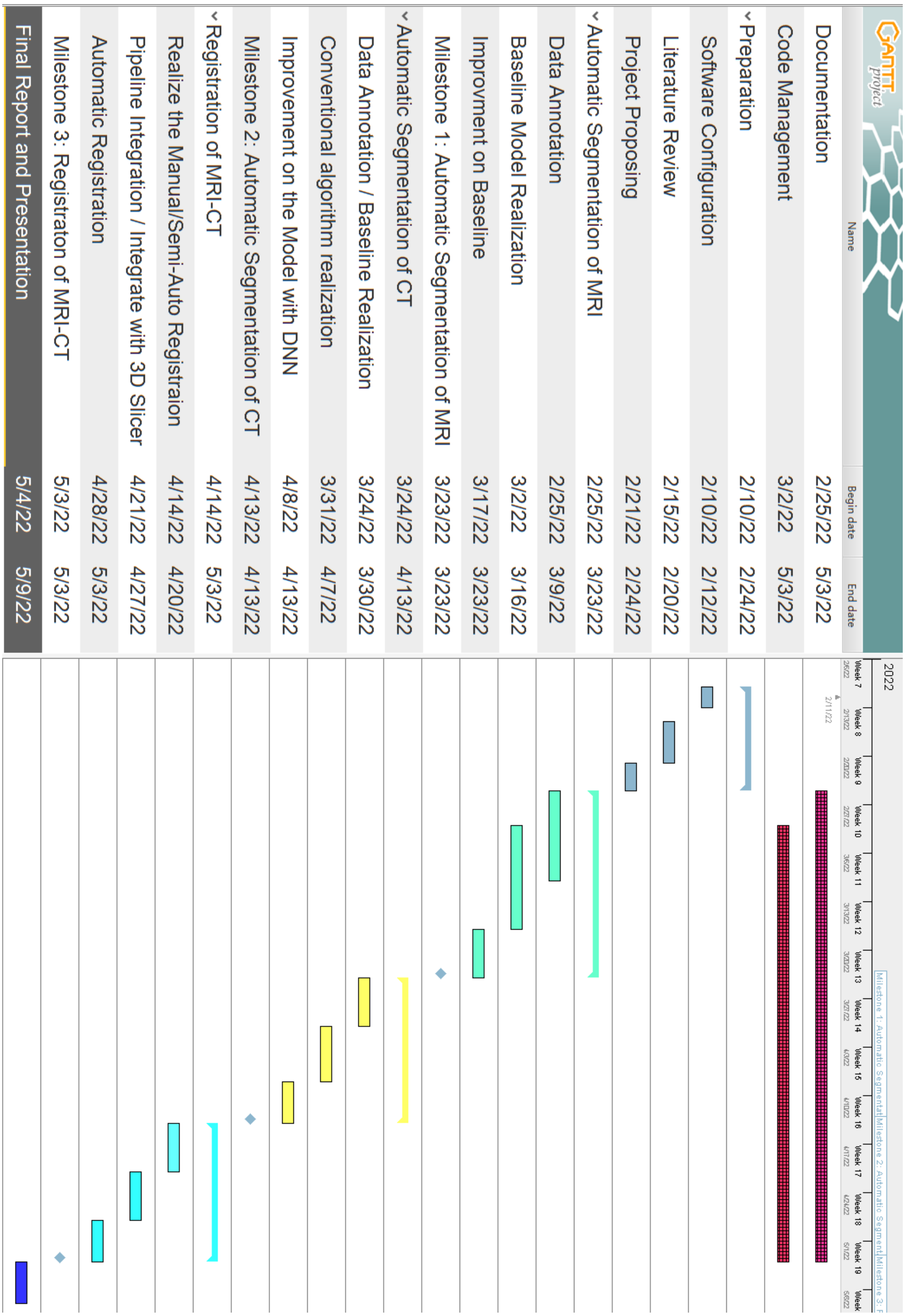

Fig. 2. Project Time Management.