Asignment Title:

Bone Segmentation Landmark Detection in 3D Knee CT

Submitted By:

Krishala Prajapati

Position: MIA Research Assistant Candidate

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Abstract

In this assignment, we segment the femur and tibia from a 3D knee CT image. We then expand the generated masks and apply random adjustments within a given limit. Afterward, we identify the lowest medial and lateral points on the tibia region in each mask. We use basic image processing techniques such as threshold-based segmentation, morphological operations for cleaning the masks, and a simple landmark-finding algorithm. The output of the assignment includes five generated masks and the coordinates of the identified landmarks.

Keywords: *3D CT segmentation, femur, tibia, morphological operations, thresholding, landmark detection*

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1. Introduction

1.1 Image Segmentation

Image segmentation can be defined as a computer vision technique that divides a given image into different segments or regions based on image characteristics such as color, intensity, and texture. This process helps simplify the image and makes it easier to analyze specific areas or regions of interest. It also plays a significant role in object detection. The algorithms used for image segmentation range from simple traditional methods to complex deep learning-based approaches.

1.2 Morphological Operations

Morphological operations are a set of techniques used in image processing to analyze and modify the shapes and structures of objects within an image. These operations are based on the mathematical theory of morphology, which focuses on the properties of shapes and patterns.

1.3 View of the 3D image

In 3D segmentation, there are three orthogonal views:

- Axial View:
  A horizontal cross-section of the body, viewed from top to bottom. This view is obtained by keeping the z-axis constant.

- Sagittal View:
  A vertical cross-section from left to right. This view is obtained by keeping the x-axis constant.

- Coronal View:
  A vertical cross-section from front to back. This view is obtained by keeping the y-axis constant.

2. Objectives

- Segment femur and tibia
- Contour Expansion
- Randomized Contour Adjustment
- Landmark Detection on Tibia

3. Data Description

The input provided was a CT scan of the knee in .nii format. A .nii file, short for NIFTI (Neuroimaging Informatics Technology Initiative), is a file format commonly used in medical imaging to store volumetric data obtained through techniques such as Magnetic Resonance Imaging (MRI) or Computed Tomography (CT). In this case, the image had a size of $512 \times 512 \times 216$.

The data was loaded for segmentation using the Nibabel library. After loading, the image was converted into a NumPy array to enable better visualization and further processing.

4. Methodology

4.1 Bone Segmentation

For bone segmentation, I used threshold segmentation, where the threshold value was determined based on the intensity distribution of the image using a histogram-based method. This approach helped separate the bones from surrounding muscles and noise. The process is entirely data-driven. Threshold segmentation is a common image segmentation technique that creates a binary image by separating objects from the background based on a pixel intensity threshold. In this case, a Hounsfield Unit (HU) threshold value of 142 was used. The HU is a quantitative measure of radiodensity used in interpreting CT images.

After applying threshold segmentation, the bone regions were extracted to create a binary mask. Then, connected components in the mask were labeled using the ndimage library. Since the femur and tibia regions were connected in the mask and appeared as one large component, we used a slicing method to split the 3D mask into femur and tibia based on the slice index along a chosen axis.

Next, the segmented femur and tibia masks were cleaned using morphological operations. Specifically, we applied a binary closing operation to fill small holes and smooth the masks. Before splitting the mask into femur and tibia, we also performed an initial cleanup step using connected component labeling to retain only the largest component (assumed to be the bone) and remove smaller noisy regions such as muscles. Finally, the cleaned femur and tibia masks were combined to generate a labeled bone mask for further processing.

4.2 Contour Expansion

For contour expansion, I first extracted the voxel spacing of the image. A voxel (volume pixel) is the smallest unit of a 3D image, similar to a pixel in 2D. The voxel spacing of the given image was:

$$\text{Voxel spacing (mm): } (0.8691, 0.8691, 2.0)$$

Since the 3D image is in Hounsfield Units (HU), we cannot directly use millimeter values to expand the contour. Instead, we convert the desired expansion in millimeters into voxel units using the image's spacing, ensuring that the dilation corresponds to a real-world physical distance.

For this assignment, we chose to expand the mask by converting the target millimeter expansion into a voxel radius:

Kernel radius (voxels): [3, 3, 1] on the x, y, and z axes respectively.

We then applied dilation, a morphological operation that adds pixels to the boundaries of objects in an image. In this case, it expanded the bone mask outward, effectively growing the contour while preserving its structure.

4.3 Randomized Contour Adjustment

First, we converted the segmented mask into a binary format for easier processing. Then, we used a distance transform to randomly expand the contour. In this method, we calculate a distance map, where each voxel in the background is assigned a value representing its physical distance (in mm) to the nearest foreground voxel—that is, the surface of the bone mask. The result is an image where every background voxel holds the distance to the closest point on the bone surface.

Next, we sample a random radius within a predefined range (e.g., 0 to 2 mm). This radius determines how far we want to expand the contour from the bone surface. Finally, we generate a new mask by selecting all voxels from the distance map whose value is less than or equal to the chosen radius. This forms a randomly expanded bone mask that still respects physical spacing.

In our case, the random radii used were:

- Using random expansion r = 1.46 mm
- Using random expansion r = 3.42 mm

4.4 Landmark Detection

For landmark detection, we first apply erosion on the mask where landmarks need to be identified. Erosion is a morphological operation that removes voxels around the boundary, effectively shrinking the object and helping to isolate the surface region.We then subtract the eroded mask from the original mask to obtain the surface voxels—the boundary of the structure. These surface voxel coordinates are then converted to real-world coordinates in millimeters using the affine transformation of the image.

To separate the medial and lateral landmarks, we calculate the midpoint of the x-coordinate range (left–right axis). Surface points with x-values less than the midpoint are classified as medial, and those with x-values greater than or equal to the midpoint are classified as lateral. From each group (medial and lateral), we identify the voxel with the lowest z-coordinate, which corresponds to the lowest point anatomically. These two points are the lowest medial and lateral landmarks on the tibia.

This method is applied to:

- The original tibia mask
- The 2 mm expanded mask
- The 4 mm expanded mask
- Two randomly expanded masks (one within 2 mm, and the other within 4 mm)

5. Results

5.1 Bone Segmentation Output:

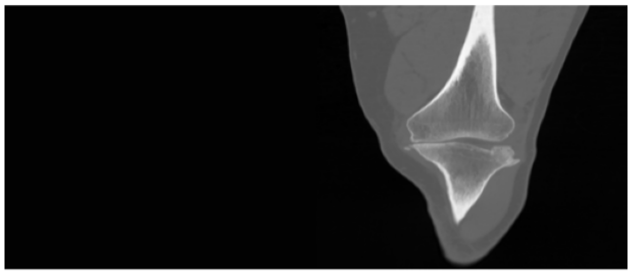

Figure 5.1: Provided CT Image

Figure 5.2: Segmented Bone Mask

Figure 5.3: Femur and Tibia labelled Mask(Upper part is femur and lower is Tibia

5.2 Contour Expansion Output:

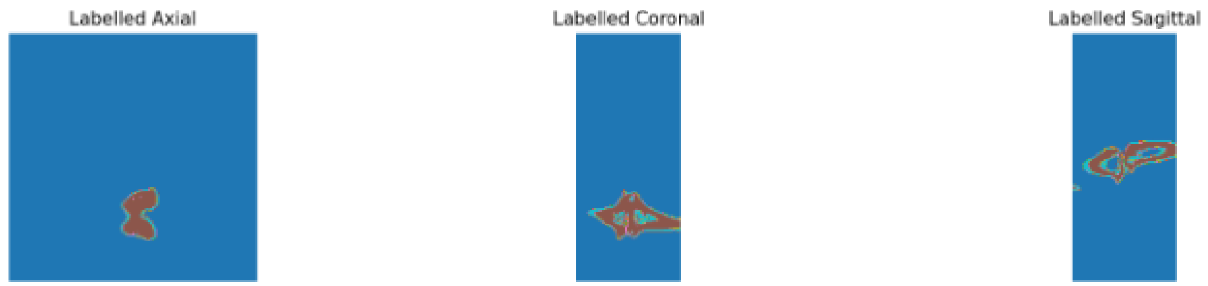

Figure 5.4: 2mm Expansion Visualization on eaxh axis where brown is original and blue is expanded

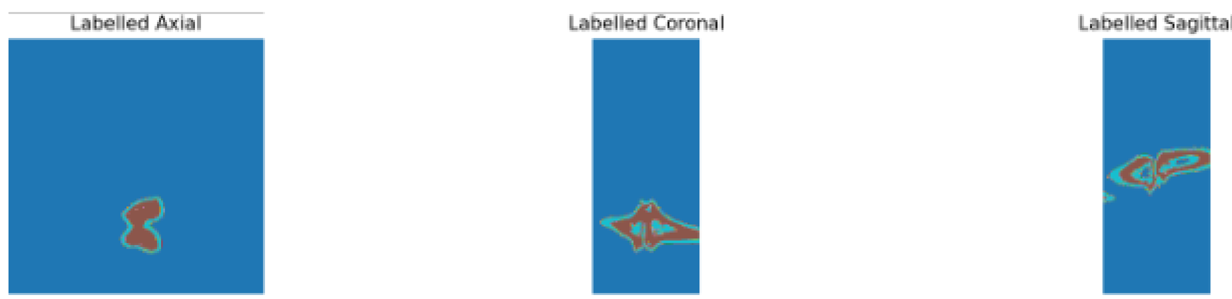

Figure 5.5: 4mm Expansion Visualization on eaxh axis where brown is original and blue is expanded

5.3 Randomized Contour Adjustment:

(a) Original Mask (b) 2mm Expanded Mask (c) Randomly Expanded Mask

Figure 5.6: Adjustment of the contour within 2mm expansion

(a) Original Mask (b) 2mm Expanded Mask (c) Randomly Expanded Mask

Figure 5.7: Adjustment of the contour within 4mm expansion

5.4 Landmark Detection Output:

Mask	Medial Lowest (x, y, z)	Lateral Lowest (x, y, z)
Original	[129.50, -30.42, -254.5]	[221.63, -26.94, -216.5]
2mm Expanded	[129.50, -29.55, -260.5]	[221.63, -26.07, -222.5]
4mm Expanded	[129.50, -28.68, -264.5]	[221.63, -25.21, -226.5]
Random 1	[129.50, -30.42, -254.5]	[221.63, -26.94, -216.5]
Random 2	[129.50, -30.42, -256.5]	[221.63, -26.94, -218.5]

Table 5.1: Coordinates of the lowest medial and lateral tibia points across different mask variations.

6. Discussion

During this assignment, the provided CT image showed the femur and tibia regions positioned very closely together. As a result, threshold-based segmentation merged both bones into a single connected region. To separate them, we had to manually split the femur and tibia using slicing techniques. I also experimented with watershed segmentation for this purpose. However, due to the hollow structure of the femur, parts of it were incorrectly segmented and merged with the tibia.

Watershed segmentation is a region-based technique that leverages image morphology. It segments regions based on pixel similarity, considering both spatial proximity and intensity values. This method is especially useful when dealing with touching or overlapping structures, irregular shapes, and when marker-based segmentation is possible. Despite its potential, watershed did not produce satisfactory results in this case due to the structural complexity of the bones.

Overall, this assignment provided valuable insight into working with 3D medical images and gave me hands-on experience with image preprocessing, segmentation, and landmark detection techniques.

7. AI Tools Usuage

During the course of this assignment, I used ChatGPT to support both my writing and technical understanding. Firstly, I utilized it to correct grammatical errors and improve the clarity of the paragraphs in my report by providing rough drafts and refining them with its assistance.

In addition to writing support, ChatGPT also helped during the coding phase. When I encountered issues such as the femur and tibia not being properly separated during segmentation, I consulted ChatGPT to understand the possible causes and explore alternative solutions. It guided me in analyzing the problem and suggested techniques like watershed segmentation.

Furthermore, as working with 3D medical images was a new experience for me, I used ChatGPT to learn how to visualize these images effectively. This helped me interpret and analyze the outputs more clearly during the segmentation and landmark detection processes.

8. Conclusion

Hence, segmentation was performed using thresholding. Additionally, contour expansion and random contour adjustments were applied, and the landmarks were successfully detected.

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