Medical Image Processing: CT Scan Analysis for Knee Region Analysis

Introduction

Image processing plays a crucial role in medical image analysis by enabling automated segmentation and contour manipulation of anatomical structures for research and clinical applications. This project specifically focuses on processing knee region CT scans to extract femur and tibia structures, expand their contours, create randomized variations, and detect anatomical landmarks. CT (Computed Tomography) scans provide detailed cross-sectional images of internal body structures using X-ray technology, with these volumetric datasets being invaluable in computer vision applications due to their high spatial resolution and excellent contrast between different tissue types using Hounsfield Units (HU) to quantify tissue density.

Project Overview and Task Description

This project focuses on comprehensive analysis of knee region CT scans, involving multiple image processing tasks including segmentation for isolating femur and tibia bones from surrounding tissue, contour expansion by systematically expanding bone contours by specified distances (2mm and 4mm), randomization by creating randomized mask variations with controlled randomness levels (20% and 80%), and landmark detection for identifying medial and lateral anatomical landmarks in the tibial plateau region. These tasks collectively enable detailed morphological analysis of knee joint structures for clinical and research applications.

Technical Approach and Methodology

Data Preprocessing and Mask Creation

The foundation of successful medical image analysis lies in data quality, with approximately 80% of effort dedicated to creating clean, accurate masks since the knee region analysis required isolation of only femur and tibia structures, treating everything else as noise. The preprocessing involved identifying bone structures using their high Hounsfield Unit values and applying morphological operations to clean noise while preserving important features. Zoom operations were performed to address granular details and enhance the resolution of specific anatomical regions. Gaussian filtering was applied to create controlled blur, which helped retain important structural details while reducing noise artifacts that could interfere with subsequent processing steps.

Segmentation Strategy

Watershed segmentation was employed as the primary method for detaching components that were too close and appeared to be connected, particularly for separating femur and tibia bones from the preprocessed masks. This algorithm treats the image as a topographic surface and creates natural boundaries between different regions through a flooding process. The technique proved effective for handling connected bone structures and was specifically used to segment tibia and fibula, which later served as input for landmark detection tasks.

Distance Transform Techniques

Two complementary distance transform approaches were utilized for contour manipulation. The Euclidean Distance Transform computes the minimum distance from each background pixel to the nearest foreground pixel, enabling uniform contour expansion by including pixels within the desired expansion distance (2mm or 4mm) from the original boundary. The Signed Distance Transform assigns distances to both foreground and background pixels, providing controlled randomization by randomly selecting pixels within specified distance ranges from the original contour while maintaining anatomical plausibility.

Landmark Detection Implementation

The landmark detection process involved multiple steps starting with skeletonization applied to each 2D slice to identify potential coordinate candidates and reduce the tibia mask to single-pixel width curves. The tibial plateau region was identified using the segmentation mask generated earlier, focusing analysis on the clinically relevant area. A midline was established by calculating the median of x-coordinates (left-right axis) to separate medial and lateral regions. Finally, coordinate selection used a weighted approach considering distance from the established midline and depth to identify optimal landmark positions.

Technology Stack

The implementation relied on established image processing libraries including scikit-image for core image processing operations, Scipy for scientific computing, opencv for computer vision techniques, Matplotlib for 2D visualization, and Mayavi for 3D visualization and volumetric rendering.

Problem-Solving Journey and Challenges

Dataset Understanding

Initial dataset comprehension required investigation of medical terminology and anatomical structures. The dataset comprised 2D axial slices, with bone structures exhibiting highest Hounsfield Unit values, providing the foundation for the segmentation strategy.

Preprocessing Challenges

Creating effective masks presented significant challenges due to threshold variability where each slice required different threshold values due to varying contrast and noise levels. Connected structures in middle slices often contained connected bone structures requiring separation techniques. Feature preservation involves balancing noise removal while retaining important anatomical features. The absence of clear bimodal distribution prevented use of standard Otsu thresholding, necessitating custom threshold selection.

Technical Problem Resolution

The solution involved combining morphological operations including erosion, dilation, opening, and closing to handle varying slice characteristics. Watershed segmentation provided reliable separation of connected bone structures. Distance transform enabled uniform contour expansion, overcoming limitations of coordinate-based extension methods. During the development process, other techniques such as flood-fill algorithms, Canny edge detection, and active contours were also attempted but did not provide satisfactory results for this specific application.

Learning Outcomes and Impact

This project provided comprehensive exposure to medical imaging challenges and advanced image processing techniques. The experience enhanced problem-solving capabilities through self-directed learning in a complex domain. Medical imaging demonstrated significant potential for further enhancement through machine learning and deep learning integration, while proving that sophisticated results remain achievable through traditional image processing methods.

AI-Assisted Development Approach

Large Language Models (ChatGPT, Claude AI, Perplexity) proved valuable throughout the development process for research acceleration by rapidly identifying relevant techniques and methodologies, idea generation and refinement to enhance creative problem-solving approach, code structure optimization to improve adherence to software development standards, and automation support by generating PowerShell scripts and documentation templates. However, limitations included initial code suggestions often requiring substantial refinement and implementation specificity requiring extensive documentation consultation for detailed implementation. The AI-assisted approach significantly accelerated learning curve navigation and provided structured development methodology while maintaining focus on core technical challenges.

Conclusion

This project successfully demonstrates the application of classical image processing techniques to complex medical imaging challenges in knee CT analysis. The comprehensive approach, combining watershed segmentation, distance transforms, and morphological operations, achieved robust results for bone segmentation, contour manipulation, and landmark detection without requiring machine learning approaches.

The methodology proves that fundamental image processing algorithms, when properly implemented and combined, can address sophisticated medical imaging tasks. The distance transform technique emerged as particularly versatile, enabling both uniform contour expansion and controlled randomization through a single mathematical framework. The integration of AI-assisted development accelerated the research and implementation process while maintaining technical rigor, presenting a valuable methodology for tackling complex medical imaging challenges.