Processing of Medical Images with Automatic Algorithms

Oltiana Seitaj

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OLTIANA SEITAJ
Department of Industrial Ingeenering,Eletronical and Mechanical
Univeristy of Studies RomaTre
Rome,Italy
oseitaj2@os.uniroma3.it

***Abstract*—The computer-based process of identifying the boundaries of lung from surrounding thoracic tissue on computed tomographic (CT) images, which is called segmentation, is a vital first step in radiologic pulmonary image analysis. Many algorithms and software platforms provide image segmentation routines for quantification of lung images. Segmentation is the process of isolating specific regions or objects within an imaged volume, so that further study can be undertaken on these areas of interest. This study basically depends on different segmenting methods and different algorithms on segmenting automatically. Some processing techniques that are used are: Normalize, Gaussian filter, Median filter, enhanced and Thresholding.**

Keywords—image processing, thresholding segmentation,machine learning.

Introduction

Segmentation and preprocessing are fundamental in the analysis of DICOM (Digital Imaging and Communications in Medicine) images, especially in medical imaging applications. Preprocessing operations enhance image quality, facilitating subsequent processing steps. Common preprocessing techniques include intensity normalization, noise reduction, contrast enhancement, image registration, image resizing, and artifact removal.

This presentation highlights the importance of preprocessing and segmentation in medical imaging, demonstrating the variability in algorithm performance and pointing towards future advancements in the field.

Our aim is to review and explain the capabilities and performance of currently available approaches for segmentation of lungs with pathologic conditions on chest CT images, with illustrations to give radiologists a better understanding of potential choices for decision support in everydaypractice.

Efficient and accurate medical image segmentation is one of the biggest challenges in modern computer vision. Nowadays, this task is often an important step in the analysis of both two-dimensional (2D) images and three-dimensional (3D) imaging datasets. Although the typical imaging datasets contain 3D structures, many traditional segmentation methods are limited to processing of individual images in a “slice-by-slice” manner. Such an approach can be prone to errors and tedious due to a large number of images in datasets. Fully 3D segmentation algorithms can offer clear improvements, eliminating the need for the processing of separate slices and providing natural continuity and smoothness of the segmented regions.

I. BRIEF OVERVIEW OF THE PROGRESS IN MEDICAL IMAGE PROCESSING

A. Introduction

Medical image processing has evolved significantly since its inception, driven by technological advancements and the growing demand for precise and efficient diagnostic tools. This overview highlights the key milestones and trends that have shaped the field.

B. Historical Development

The journey of medical image processing began in the mid-20th century with the development of imaging modalities like X-rays and CT scans. The introduction of MRI in the 1970s marked a significant milestone, providing high-resolution images of soft tissues.

C. Early Techniques

Initially, image processing techniques were simple, focusing on image enhancement and basic edge detection to improve visual clarity. Methods like histogram equalization and basic filtering were widely used.

D. Advent of Digital Image Processing

The 1980s and 1990s saw the rise of digital image processing, enabling more sophisticated techniques such as image segmentation and registration. These advancements facilitated the automatic delineation of anatomical structures and the alignment of images from different modalities.

E. Emergence of Machine Learning

In the 2000s, machine learning techniques started gaining traction. Algorithms like support vector machines (SVMs) and random forests were applied to classify medical images, improving diagnostic accuracy and efficiency.

F. Revolution with Deep Learning

The 2010s ushered in the era of deep learning, revolutionizing medical image processing. Convolutional neural networks (CNNs) and other deep learning models significantly enhanced capabilities in image segmentation, classification, and anomaly detection. Techniques like U-Net became standard for tasks such as tumor segmentation in MRI scans.

G. Current Trends

Today, the integration of artificial intelligence, big data, and cloud computing is transforming medical image processing. AI-driven tools are being integrated into clinical workflows, providing real-time decision support and improving patient outcomes. Emerging trends include the development of explainable AI models, which aim to make the decision-making process of AI systems more transparent and understandable.

H. Impact on Healthcare

These advancements have greatly impacted healthcare, leading to more accurate diagnoses, personalized treatment plans, and improved patient monitoring. Image-guided surgery, for instance, has become more precise, reducing the risk of complications and enhancing recovery times.

I. Conclusion

The progress in medical image processing reflects a dynamic interplay between technological innovation and clinical needs. As the field continues to evolve, it holds great promise for further transforming medical diagnostics and treatment, ultimately improving patient care.

II. DETAILED OVERVIEW OF THE METHODS AND TECHNOLOGIES USED FOR TUMOR SEGMENTATION

Radiologists use several advanced techniques for lung tumor segmentation in clinical practice today. These techniques leverage both traditional image processing and cutting-edge machine learning approaches. Here are some of the latest techniques:

A. Manual Segmentation

- Radiologist Expertise

Traditionally, radiologists manually outline the tumor boundaries on each slice of the medical image (e.g., CT or MRI scans). This method is highly accurate but extremely time-consuming and subject to inter-observer variability.

- Tools

Specialized software with drawing tools to assist radiologists in manually outlining the tumor.

B. Thresholding and Region Growing

Traditional methods like thresholding and region growing are still in use, especially for simple cases. These methods are based on setting intensity thresholds or growing regions from seed points based on predefined criteria.

- Intensity Thresholding:

Uses pixel intensity values to differentiate between tumor and normal tissue. This method assumes that the tumor has a distinct intensity compared to the surrounding lung tissue.

- Adaptive Thresholding:

Adjusts the threshold value based on local image characteristics, providing better results in cases where tumor and tissue intensities overlap.

- Morphological Operations

Morphological operations such as dilation, erosion, opening, and closing are used to refine segmented regions, remove noise, and enhance the structure of the segmented tumors.

- Region Growing:

Starts from a seed point within the tumor and grows the region by adding neighboring pixels that have similar intensity values.

- Watershed Segmentation:

Treats the image as a topographic surface and finds the watershed lines to segment different regions.

- Canny Edge Detection:

Identifies edges in the image by looking for areas of rapid intensity change, helping to delineate the tumor boundaries.

- Active Contour Models (Snakes):

Iteratively evolves a contour to fit the edges of the tumor based on image gradients and external constraints.

- Machine Learning and Deep Learning

Convolutional Neural Networks (CNNs): CNNs, especially fully convolutional networks (FCNs), U-Net, and its variants, are widely used for their ability to learn hierarchical features directly from raw imaging data. Deep learning models specifically designed for image data. CNNs can automatically learn features from raw image data, significantly improving segmentation accuracy.

III. PREPROCESSING OF DICOM IMAGES

Preprocessing involves a series of operations applied to the raw DICOM images before further analysis. These operations are designed to improve the quality of the images and facilitate subsequent processing steps. Common preprocessing techniques include:

A. Intensity normalization:

Ensuring consistent intensity levels across different images

B. Noise reduction:

Removing or reducing noise that may be present in the images due to various factors such as sensor characteristics, acquisition conditions, or transmission artifacts.

C. Contrast enhancement:

Increasing the visibility of structures of interest by enhancing the contrast between different regions of the image.

D. Image registration:

Aligning multiple images acquired from different modalities or at different time points to a common coordinate system.

E. Imageresizing:

Rescaling images to a consistent size or resolution for analysis

F. Artifact removal

Removing artifacts such as motion artifacts, patient motion, or hardware-related artifacts.

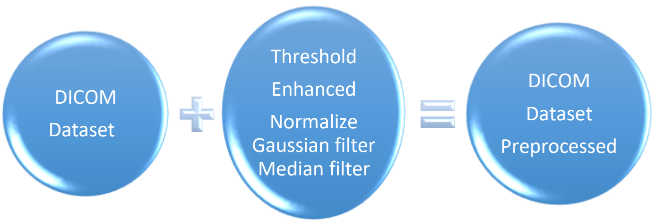

Fig.1 Workflow represents the basic steps.

IV. SEGMENTATION OF DICOM IMAGES

Segmentation refers to the process of partitioning an image into meaningful regions or objects. In the context of DICOM images, segmentation is often used to delineate anatomical structures, lesions, or abnormalities. Accurate segmentation is crucial for tasks such as organ volume measurement, tumor detection, and treatment planning. Common segmentation techniques include:

A. Thresholding:

Separating regions of interest based on their intensity values relative to a threshold.

B. Region growing

Growing regions from seed points based on similarity criteria such as intensity or texture.

C. Edge-based segmentation:

Detecting boundaries between different regions using edge detection algorithms.

D. Clustering

Grouping pixels or voxels into clusters based on similarity measures.

E. Active contour models (snakes):

Deformable models that iteratively evolve to capture object boundaries

F. Deep learning-based segmentation

Using convolutional neural networks (CNNs) or other deep learning architectures to learn complex mappings from image data to segmentation masks.

V. IMPORTANCE OF SEGMENTATION AND PREPROCESSING TECHNIQUES

Preprocessing and segmentation are crucial steps in image analysis and computer vision tasks, including medical image analysis. Here are some reasons why these steps are important:

A. Improvement of Image Quality:

Medical images often contain noise, artifacts, and variations in contrast that can obscure important details. Preprocessing techniques, such as filtering, normalization, and enhancement, help improve image quality by removing noise and enhancing important features, ensuring clearer and more accurate interpretation.

B. Noise Reduction:

Images acquired from real-world sources often contain noise due to various factors such as sensor imperfections, lighting conditions, and transmission artifacts. Preprocessing techniques like filtering and denoising help in reducing noise, which can improve the accuracy of subsequent analysis.

C. Enhancement of Features:

Preprocessing techniques like contrast enhancement and histogram equalization can enhance the visibility of important features in images. This is particularly important in medical imaging where subtle details can be critical for diagnosis.

D. Accurate Diagnosis:

Segmentation techniques help in isolating specific structures or regions of interest (ROI) in medical images, such as tumors, organs, or blood vessels. By delineating these regions accurately, it allows clinicians to measure sizes, shapes, and other critical parameters, which are vital for accurate diagnosis and treatment planning.

E. Normalization:

In many cases, images may have variations in intensity or scale. Normalization techniques ensure that images are standardized in terms of intensity levels and dynamic range, making them more suitable for quantitative analysis and comparison.

F. Improving Segmentation Accuracy

Segmentation is the process of partitioning an image into meaningful regions or objects. Preprocessing techniques like edge enhancement, contrast adjustment, and noise reduction can improve the accuracy and robustness of segmentation algorithms by making object boundaries more distinct and reducing the impact of noise.

G. Removing Irrelevant Information:

Preprocessing techniques can help in removing irrelevant or distracting information from images, focusing the analysis on the relevant features of interest. For example, in medical imaging, preprocessing can help remove artifacts or non-tissue structures, allowing segmentation algorithms to focus on delineating specific organs or abnormalities.

H. Adaptation to Algorithm Requirements:

Different segmentation algorithms may have different requirements and assumptions about the input data. Preprocessing techniques can help in preparing the data to meet these requirements, thereby improving the compatibility and effectiveness of segmentation algorithms.

I. Facilitating Automation:

Preprocessing techniques can automate certain aspects of data preparation, making the overall analysis pipeline more efficient and scalable. By automating tasks such as noise reduction and normalization, researchers can focus more on the interpretation and analysis of results.

In summary, preprocessing and segmentation are essential steps in image analysis pipelines, playing a critical role in improving the quality, accuracy, and interpretability of the results. These steps help in extracting meaningful information from images, enabling a wide range of applications in fields such as medical diagnosis, object recognition, and scene understanding. Also preprocessing prepares DICOM images for analysis by enhancing their quality and removing unwanted artifacts, while segmentation extracts meaningful information from the images by partitioning them into relevant regions or objects.

VI. APPLYING OF PREPROCESING AND SEGMENTATION TECHNIQUES

1.Obtain images.The directory contains 148 medical images in DICOM format.

2.Upload DICOM directory to MATLAB.
3.Read DICOM images. Begin preprocessing and segmentation steps
4.Perform thresholding to create mask
5.Convert binary mask to grayscale
6.Apply image Enhancement.
7.Normalization: The mat2gray function is used to normalize the intensity values of the mask to the range [0,1].
8.Gaussian Filtering: imgaussfilt applies Gaussian filtering to the normalized image. Gaussian filtering helps to remove noise and smoothen the image.
9.Median Filtering:medfilt2 applies median filtering to the Gaussian filtered image. Median filtering is effective in removing salt-and-pepper noise while preserving edges.
10.Convert enhanced image to DICOM format
11.Analysis of Data

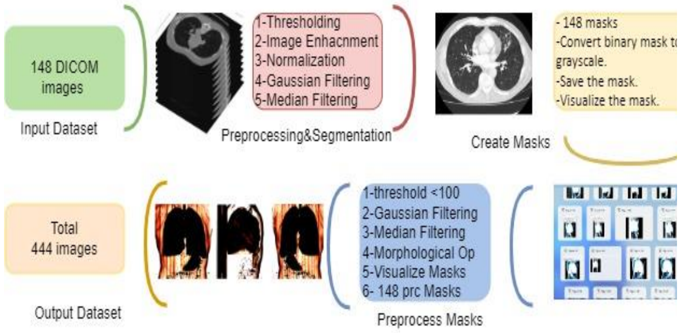

Fig.2 This flowchart provides a basic overview of the segmentation and preprocessing pipeline for DICOM images.

a) Apply Preprocessing to Images and Masks

Fig.3 Preprocessed masks

Masks of images with threshold <100

Masking images and applying a threshold less than 100 is very important for image processing and analysis. It helps in isolating regions of interest. Masking involves creating a binary mask that highlights specific regions or structures of interest in an image while masking out the rest. This helps in focusing the analysis on the relevant areas and ignoring irrelevant background information.

VII. EVALUTION OF THE SEGMENTATION

To assess the quality of segmentations, several parameters and metrics can be used. These metrics can be computed by comparing the segmentation results with ground truth data.To proceed with the computation of these metrics using the provided image, it needs:

1. The segmentation results of the image.

2. The ground truth segmentation of the same image

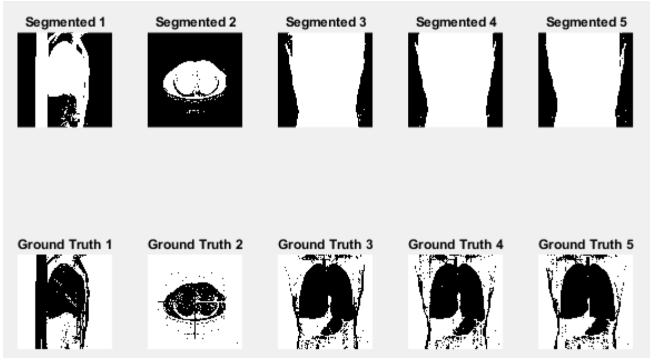

Fig.4 Interpretation of the DSC Values:

A. Range of Values:

The DSC values now range from approximately 0.0345 to 0.3483.

The higher values indicate a better overlap between the segmented masks and ground truth masks, while lower values indicate less overlap.

B. Low DSC Values (around 0.0345 - 0.1089):

These low values suggest poor agreement between the segmented masks and the ground truth masks for some images.Possible reasons for low values include:

1) Errors in segmentation.
2) Misalignment between segmented masks and ground truth masks.
3) Issues with binarization or resizing.

C. Moderate DSC Values (around 0.1818 - 0.2418):

These moderate values indicate some level of overlap but still show room for significant improvement. These values might indicate that the segmentation algorithm is capturing some features correctly but missing others.

D. Higher DSC Values (around 0.2777 - 0.3483):

These higher values indicate relatively good agreement between the segmented and ground truth masks.

These values suggest that the segmentation algorithm is performing reasonably well for these particular images.

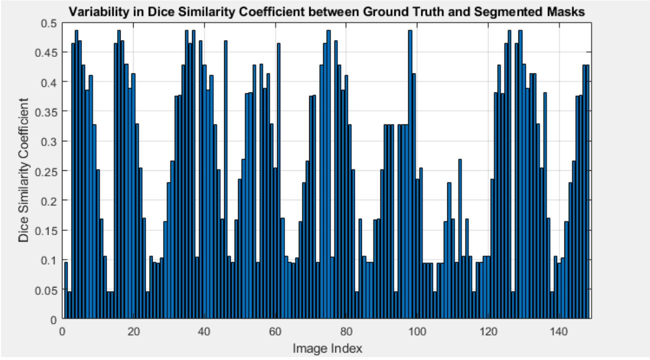

Fig.5 By examining this plot, we can observe the distribution and variability of DSC values across different images. Higher DSC values indicate better agreement between the ground truth and segmented masks, while lower values indicate poorer agreement or more variability.

VIII. CONCLUSIONS

This work performs several operations on a set of DICOM images located in a directory. Setting up the directory and reading DICOM files, reallocating cell array for masks, looping through DICOM files, reading DICOM image, thresholding to create a mask. Thresholding operation: Creates a binary mask where pixels with intensity greater than 100 are set to 1, and others to 0. Converting binary mask to grayscale. Converts the binary mask to grayscale by multiplying it by 255 and converting it to an 8-bit unsigned integer (uint8). Saving the mask. Visualizing the mask. Opens a new figure and displays the mask image. Sets the title of the figure to indicate the corresponding image index. Load preprocessed masks. Apply histogram equalization for enhancement. Overall, it reads each DICOM image from the specified directory, applies a thresholding operation to create a binary mask, converts the binary mask to grayscale, saves the mask in a cell array, apply histogram equalization for enhancement, perform histogram equalization on each preprocessed mask(this enhances the contrast of the image) and visualizes the mask for each DICOM image in a separate figure.

IX. FUTURE WORK

Segmentation of voxels tumors in lungs

The segmentation of voxel-based tumors in the lungs is a critical area of research in medical imaging and oncology. Segmenting voxels of tumors in the lungs involves identifying and delineating the three-dimensional regions of interest within the medical imaging data. It involves identifying and delineating regions of interest (ROIs) within 3D volumetric data acquired from imaging modalities such as CT (Computed Tomography) or MRI (Magnetic Resonance Imaging). This process is crucial for diagnosis, treatment planning, and monitoring of lung cancer. Below are listed some techniques how it can be done:

A. *Image Acquisition and Preprocessing*

Image acquisition is the initial step, where imaging modalities such as CT and MRI are used to capture detailed volumetric data of the lungs. However, raw images are often noisy and contain artifacts that may hinder accurate segmentation. Therefore, preprocessing is a vital step that includes:

- Noise Reduction: Techniques like Gaussian smoothing, median filtering, or anisotropic diffusion are applied to reduce noise while preserving important structural details.
- Normalization: Standardizing the intensity values across different scans ensures consistency in subsequent segmentation steps, especially when images come from different machines or protocols.
- Lung Field Extraction: Segmenting the lung field from the background and other structures helps to focus the segmentation algorithm on the region of interest.
- Contrast Enhancement: Methods like histogram equalization or adaptive histogram equalization can enhance the contrast of images, making tumor boundaries more distinguishable.

B. *Thresholding and Region Growing*

Thresholding is one of the simplest segmentation techniques that separates voxels based on their intensity values. For lung tumor segmentation:

- Thresholding: A global or adaptive threshold is set to differentiate between the tumor and non-tumor tissues. However, lung tumors often have varying intensities, making simple thresholding less effective.
- Region Growing: Starting from a seed point (usually selected within the tumor), this method iteratively grows the region by including neighboring voxels that have similar intensity values. The process stops when no more similar voxels are found. Region-growing methods work well for tumors with homogeneous textures but may struggle with highly heterogeneous or complex structures.

C. *Watershed Transform*

The Watershed Transform is a powerful technique used for segmenting objects in images with varying intensities:

- **Watershed Segmentation**: This technique treats the image as a topographic surface, where the voxel intensity represents elevation. The algorithm identifies "catchment basins" (regions of interest) and "watershed lines" (boundaries). Watershed segmentation is particularly useful for separating touching or overlapping structures.
- **Markers and Morphological Operations**: Markers can be placed in areas of interest to guide the watershed algorithm, reducing over-

segmentation. Preprocessing steps such as morphological operations (e.g., erosion and dilation) can help enhance the segmentation quality

D. Graph Cut Algorithms

Graph cut algorithms use graph theory to perform image segmentation:

- Graph Representation: The image is modeled as a graph where each voxel is a node connected by edges. The weights of the edges represent the similarity between voxels.
- Min-Cut/Max-Flow Algorithm: This method finds the optimal cut that separates the graph into segments by minimizing a cost function. This approach can handle complex shapes and intensity variations well.
- Interactive Segmentation: Sometimes, user input is required to refine the segmentation results. Interactive graph cut algorithms allow users to provide manual constraints, which are particularly helpful for difficult cases.

E. Machine Learning-Based Approaches

Machine learning (ML) and deep learning (DL) have revolutionized medical image segmentation, providing more robust and accurate solutions:

Traditional Machine Learning: Techniques like Random Forests, Support Vector Machines (SVMs), and k-Nearest Neighbors (k-NN) are used to classify each voxel based on handcrafted features (e.g., intensity, texture, shape). These models require extensive feature engineering and are limited by the choice of features.

Deep Learning Models: Convolutional Neural Networks (CNNs), U-Nets, V-Nets, and fully convolutional networks (FCNs) are popular for end-to-end segmentation. These models learn features directly from the data, eliminating the need for manual feature extraction. They can capture complex patterns and variations in tumor shape, size, and texture.

3D Convolutional Neural Networks: Unlike 2D CNNs, 3D CNNs work directly with volumetric data, improving spatial consistency in segmentation results.

Attention Mechanisms and Transformer Models: Advanced models use attention mechanisms to focus on relevant areas within the image, improving segmentation accuracy in cases with unclear boundaries or heterogeneous tumor textures.

Generative Adversarial Networks (GANs): GANs are increasingly used to generate high-quality segmentations and synthetic data to augment training datasets, especially in data-scarce environments.

F. Manual Adjustment

While automated segmentation techniques have advanced significantly, manual adjustments by radiologists and medical experts are often necessary to ensure clinical accuracy:

Expert Review and Refinement: After automated segmentation, clinicians review and adjust the segmentation results to correct any inaccuracies, especially for challenging cases involving small, irregularly shaped, or ambiguous tumors.

Semi-Automatic Approaches: Some tools combine automated and manual segmentation, allowing clinicians to interactively adjust boundaries, add or remove regions, and refine segmentation iteratively.

G. Quantitative Analysis After Segmentation

After segmentation, the resulting voxel-based representation of the tumor can be further analyzed for various quantitative measurements, such as:

Volume and Size Measurements: Determining the exact size and volume of the tumor is crucial for staging cancer, assessing its growth rate, and evaluating treatment efficacy.

Shape Features: Irregularity, sphericity, and compactness are some shape features that can provide insights into tumor behavior and potential malignancy.

Texture Features: Analyzing the texture of the segmented tumor (e.g., using gray-level co-occurrence matrices, Haralick features) can reveal heterogeneity, which may correlate with tumor aggressiveness.

Spatial Relationships with Surrounding Structures: Understanding how the tumor interacts with nearby anatomical structures (e.g., blood vessels, bronchi) is vital for surgical planning and radiotherapy.

H. Future Directions in Voxel-Based Tumor Segmentation of Lungs

The future of voxel-based lung tumor segmentation is poised to benefit from several emerging technologies and approaches:

- **Hybrid and Ensemble Methods**: Combining multiple segmentation techniques (e.g., deep learning with graph cuts or region growing) can leverage the strengths of each method, improving robustness and accuracy.
- **Federated Learning for Privacy-Preserving Segmentation**: To address data privacy concerns, federated learning allows models to be trained on decentralized data from multiple institutions without sharing sensitive patient information.
- **Real-Time Segmentation for Interventional Use**: Research is progressing towards real-time segmentation that can be integrated into interventional radiology and robotic-assisted surgeries, allowing for precision targeting of tumors.
- **Uncertainty Quantification**: Developing models that provide uncertainty estimates along with segmentation results can help clinicians assess the reliability of the predictions and make better-informed decisions.
- **Radiomics and Radiogenomics Integration**: Integrating voxel-based segmentation with radiomic and genomic data will enable more personalized and precise oncology, correlating imaging features with molecular markers.

I. Conclusion

Voxel-based segmentation of lung tumors is a rapidly evolving field that plays a crucial role in modern oncology and precision medicine. With continuous advancements in AI, imaging techniques, and computational resources, segmentation methods are becoming more accurate, efficient, and clinically applicable, promising improved patient outcomes in lung cancer diagnosis and treatment.

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