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An Overview of Medical Image Segmentation Algorithms

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Abstract: Many medical imaging applications rely on image segmentation to automate or facilitate the delineation of anatomical features and other regions of interest. The results of segmentation have a significant impact on all subsequent image analysis operations, including object representation and description, feature measurement, and even higher-level tasks like object classification. As a result, image segmentation is the most important and fundamental step in aiding the identification, characterization, and visualization of regions of interest in any medical image. The radiologist's manual segmentation of the medical image is not only a time-consuming and inefficient procedure, but it is also inaccurate, especially with the growing number of medical imaging modalities and the unmanageable number of medical images to be analyzed. It is also vital to assess current picture segmentation approaches, especially for medical images, to ensure that automated algorithms are accurate and require as little user intervention as possible. The anatomical structure or region of interest must be delineated and extracted during the segmentation process so that it can be seen separately. This study focuses on the concept that underpins the basic approaches used. Image segmentation may be divided into two types: semi-interactive and entirely automatic, and the techniques developed fit into either of these categories.

Keywords: medical imaging, segmentation, thresholding, region growing, ROI, clustering.

Introduction

An image is essentially a two-dimensional function of spatial coordinates, $f(x, y)$, whose amplitude at a particular point determines the image's intensity value. The picture can be described as the sum of illumination and reflection functions:

$f(x,y) = i(x,y) \,.\, r(x,y)$[1],

Where $i(x,y)$ is the function of intensity and $r(x,y)$ is the function of reflectivity.

In medicine, medical imaging is a useful tool. Other imaging techniques, such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound imaging (US), provide more accurate information about the structure of the human body. These technologies become more critical in diagnosis and treatment planning. Some computer algorithms are applying for the description of anatomical structures and other regions of interest are becoming increasingly important in assisting and automating specific radiological tasks. These picture segmentation techniques are used in a variety of biomedical imaging applications, such as studying anatomical structure. Locate the tumor and any abnormalities in the region of interest. To determine the tumor's growth rate, measure the volume of the tissue (also decrease in size of tumour with treatment), Aid in treatment planning prior to radiation therapy and in calculating radiation dose [1].

The increasing size and volume of medical pictures has demanded the use of computers to speed up processing and analysis. Computer algorithms for delineating anatomical structures and other areas of interest, in particular, are becoming more significant in helping and automating specialized radiological procedures. Image segmentation algorithms are used in a variety of biomedical imaging applications, including diagnosis (1), tissue volume quantification (2), pathology localization (3), anatomical structure investigation (4), treatment planning (5), and computer-integrated surgery (6). An overview of algorithms for computer-assisted or computer-automated segmentation of anatomical medical images is presented in this work.

Literature Survey

Using dimension decomposition, X. Zhang et al devised a multi-scale 3D Otsu segmentation algorithm [2]. The method works in numerous iterations and takes into account image spatial information. One it eration's output is used as input for the next iteration. After applying a Laplacian filter to produce different image scales, 3D Otsu is utilized to generate segmentation maps. To create a final segmented image, the maps are blended. The key benefits of this approach include improved image segmentation, lower noise levels for both bi-level and multi-level thresholding, and less time complexity than previous thresholding algorithms. In [3,] clustering approaches for medical image segmentation, specifically for MR images of the brain, are reviewed, and they are effective in merging fuzzy c means with k-means to produce a novel fuzzy-k means algorithm.There are a few restrictions to the algorithm that has been developed. [4] proposes a hybrid technique for medical image segmentation that primarily uses fuzzy-c means and otsu's method after applying a vector median filter for segmentation and has attempted to demonstrate the robustness of their method by adding various types of noise to the image and obtaining satisfactory results.[5] presents a method for segmenting human retinal pictures. The information in the retina is critical for diagnosing a variety of eye illnesses. The eye's structure, namely the veins in theeye, are extremely fragile and tiny, making segmentation with conventional methods extremely challenging. The author presents a technique for segmenting the retina of the eye using a combination of filters and unsupervised learning. Phase of enhancement Matched filter (MF), Frangi's filter (FF), and Gabor wavelet filter (GF) are used in combination for combination purposes, while fuzzy c-means and ORSF to optimize threshold are employed for segmentation. MF improves vascular structures through convolution, GF improves vascular structures by calculating eigen values that represent vascular structures, and GF improves tiny vessels because it is less susceptible to noise. [6] offer an unsupervised learning approach for segmenting medical images and determining the local centre of mass of an image signal. The pixels are divided into areas based on their center of mass in this method. The authors presented this approach for 1D, obtaining a complexity of O(N), and then expanding it to higher dimensions (2D, 3D) by iterating the algorithm for each case.They compared their method to existing techniques such as the watershed method, SLIC, and GMM-HMRF, and found that their method produced less over segmentation and better region borders. Among other strategies, the suggested method received the greatest optimal-dice score, and they have demonstrated that their way of segmentation beats other unsupervised methods through quantitative and qualitative validation. [11] Preprocessed and Segmented of digital mammogram for early detection of breast cancer.]

Image Segmentation

Image segmentation is a mid-level image analysis technique that can be defined as a technique for classifying or clustering an image into several disjoint parts by grouping pixels to form a homogeneous region based on pixel characteristics such as gray level, color, texture, intensity, and other features. The primary goal of the segmentation procedure is to obtain additional information in the image's region of interest, which aids in the annotation of the object scene. [7]. Picture segmentation tries to divide an image into a set of visually distinct and homogenous sections based on specific criteria in a domain-independent manner. [8]. Segmentation's major purpose is to clearly distinguish the object from the background in a picture.

Image Segmentation Algorithms

We divide segmentation methods into eight categories:

1) thresholding;
2) region growing;
3) classifiers;
4) clustering;
5) Markov random field (MRF) models;
6) artificial neural networks;
7) deformable models;
8) atlas-guided approaches;

Other noteworthy methods that do not fit into any of these categories are listed at the end of this section. Thresholding, classifier, clustering, and MRF techniques are pixel classification methods among the methods mentioned in this section.

Medical Image Segmentation Algorithms				
Thresholding based	**Region based**	**Edge based /Boundary based**	**Clustering methods**	**Other methods**
Local thresholding; Otsu's method; Gaussian mixture method;	Region growing; Region splitting and merging;	Edge detection (1^{st} order); Prewitt, Sobel and Canny Operator; Laplacian of Gaussian(2^{nd} order); Watershed;	K-means algorithm; Fuzzy c-means algorithm; Expectation maximization(EM) algorithm; Unsupervised segmentation based on local centre of mass;	Level set method; Artificial neural networks(ANN's); Atlas guided approach; Genetic algorithm;

Fig1: Medical Image segmentation techniques

Thresholding. Thresholding is a method of segmenting scalar images by dividing the image intensities into binary partitions. Thresholding is a basic but efficient method for segmenting photographs in which various structures have varying intensities or other quantitative characteristics. Thresholding is frequently employed as the first operation in a series of image processing operations. It's been used in digital mammography, where there are usually two types of tissue present: healthy and tumorous. Its main drawbacks are that it can only generate two classes in its most basic form and that it cannot be used with multichannel pictures. Furthermore, thresholding does not usually take into account an image's spatial properties. As a result, it is susceptible to noise and intensity inhomogeneities that can occur in MR pictures. Both of these distortions effectively degrade the image's histogram, making separation more difficult. For these reasons, for medical-image segmentation, modifications on traditional thresholding that add information based on local intensities and connectedness have been proposed. A survey of thresholding methods can be found elsewhere.

Region Growing. A technique for extracting an image region that is connected based on some predetermined criteria is known as region expanding. These criteria can be based on image edges and/or intensity information. In its most basic version, region growth necessitates the manual selection of a seed point by an operator, who then extracts all pixels associated to the initial seed based on predetermined parameters. Region growth, like thresholding, is rarely employed alone, but rather as part of a collection of image-processing processes, especially for the delineation of small, basic entities like tumors and lesions. The fundamental disadvantage of area growing is that obtaining the seed point necessitates manual intervention. As a result, a seed must be planted for each location that has to be retrieved. Splitand-merge is a region-growing technique that does not require the use of a seed point.

Classifiers. Classifier methods are pattern recognition approaches that use data with known labels to partition a feature space produced from an image. A feature space is the range space of any image function, with the picture intensities themselves being the most frequent feature space. Classifiers are referred to as supervised methods since they require manually segmented training data that is subsequently utilized as a reference for segmenting fresh data automatically. The use of training data in classifier algorithms can be done in a variety of ways. The nearest-neighbor classifier is a simple classifier that assigns each pixel to the same class as the training datum with the highest intensity. The pixel is categorized into the same class as the majority of the k-closest training data in the k-nearest-neighbour classifier, which is a generalization of this approach. Because it makes no underlying assumptions about the statistical structure of the data, the k-nearest-neighbor classifier is termed a nonparametric classifier. The Parzen window is a nonparametric classifier that uses a weighted decision process to classify data inside a preset window of the feature space, centered on the unlabeled pixel intensity. The maximum-likelihood or Bayes classifier is a typical parametric classifier. The pixel intensities are assumed to be independent samples from a combination of probability distributions, often Gaussian. The probability density function describes this mixture, which is referred to as a finite mixture model:

$$f(y_j;\theta,\pi)=\sum_{k=1}^{K}\pi_k f_k(y_j;\theta_k)$$

Where$y_j$is the intensity of pixel j,$f_k$is a component probability density function parameterized by θ_k, and $\theta = [\theta_1,...,\theta_k]$. The $\pi_k$variables are mixing coefficients that weight the contribution of each density function and $\pi = [\pi_1,...,\pi_k]$. Training data is gathered by taking representative samples from each component of the mixture model and then estimating each *k*. This entails calculating k-means, covariances, and mixing coefficients for Gaussian mixtures. In order to classify fresh data, each pixel is assigned to the class with the highest posterior probability. When the data is really distributed in a finite Gaussian mixture, the maximum-likelihood classifier can perform well and provide a soft segmentation built of posterior probabilities.

Clustering. Without the need of training data, clustering algorithms fundamentally fulfill the same purpose as classifier methods. As a result, they are referred to as unsupervised approaches. Clustering algorithms iteratively alternate between segmenting the image and describing the attributes of each class to compensate for the absence of training data. Clustering algorithms, in a sense, train themselves by utilising the data given. The k-means or ISODATA method, the fuzzy c-means algorithm, and the expectation-maximization (EM) algorithm are three extensively used clustering techniques. The k-means clustering algorithm clusters data by computing a mean intensity for each class iteratively and segmenting the image by classifying each pixel in the closest mean class.

Markov Random Field Model. MRF modeling is a statistical model that can be utilized within segmentation methods, not a segmentation method in and of itself. MRFs simulate spatial interactions between pixels that are close together. These local correlations can be used to model a wide range of visual features. They are commonly employed in medical imaging since most pixels belong to the same class as their neighbors. In physical terms, this means that under the MRF assumption, any anatomical structure with only one pixel has a very low likelihood of developing. MRFs are frequently used in clustering segmentation methods like the K-means algorithm, which is based on a Bayesian prior model. The segmentation is then obtained by maximizing the segmentation's a posteriori probability given the picture data. Proper selection of the parameters governing the degree of spatial interactions is a challenge with MRF models. An extremely smooth segmentation and loss of crucial structural elements can arise from a setting that is too high. Furthermore, MRF approaches frequently necessitate computationally complex algorithms. Despite these drawbacks, MRFs are commonly utilized to model not only segmentation classes, but also intensity in homogeneities in MR images and textural qualities, which are important in digital mammography segmentation.

Artificial Neural Networks. Artificial neural networks (ANNs) are networks of parallel processing components or nodes that mimic biological learning. In an ANN, each node is capable of executing simple calculations. The adaption of weights assigned to the connections between nodes is how learning is accomplished. ANNs are a machine learning paradigm that may be applied to picture segmentation in a variety of ways. In medical imaging, the most often utilized application is as a classifier, in which the weights are calculated using training data and the ANN is then used to segment new data. ANNs can be used as a clustering tool and for deformable models in an unsupervised manner. Spatial information may be easily included into a neural network's categorization operations due to its many interconnections. Despite the fact that ANNs are naturally parallel, they are typically simulated on a serial computer, decreasing the potential computing advantage.

Deformable Models. Deformable models are model-based strategies for designating region borders utilizing closed parametric curves or surfaces that deform under the influence of internal and external pressures that are physically driven. In order to demarcate an object boundary in an image, a closed curve or surface must be put near the desired border and then allowed to relax iteratively. Internal forces are calculated from within the curve or surface to keep the deformation smooth. The curve or surface is frequently driven toward the intended feature of interest using external forces obtained from the image. In the segmentation of medical pictures, deformable models have been frequently used. Deformable models have also been employed in cardiac image segmentation, CT image bone segmentation, and ultrasound image segmentation. Deformable models are particularly well adapted to motion-tracking tasks, which are ubiquitous in ultrasonic imaging, due to their dynamic character. The ability to directly build closed parametric curves or surfaces from images and the integration of a smoothness requirement that gives robustness to noise and spurious edges are the key advantages of deformable models. They have the drawback of requiring manual interaction to set up an initial model and select appropriate parameters. Reduced sensitivity to initiation has been a study area that has yielded great results.

Atlas-Guided Approaches. When a standard atlas or template is available, atlas-guided techniques are a powerful tool for medical image segmentation. The atlas is created by accumulating anatomy information that has to be segmented. This atlas is then used to segment new pictures as a reference frame. Atlas-guided techniques are conceptually similar to classifiers; however they are implemented in the image's spatial domain rather than in a feature space. Atlas-guided techniques have mostly been used in MR brain imaging to segment distinct regions and derive the brain volume from head scans. One advantage of atlas-guided techniques is that labels and segmentation are both transferred. They also provide a common framework for analyzing morphometric parameters. Due to anatomical variability, establishing correct segmentations of complex structures is difficult even with nonlinear registration approaches. As a result, atlas-guided techniques are more suited for segmentation of structures that are stable across the study population. The use of probabilistic atlases is one way for modeling anatomical variability, although it takes more time and interaction to collect data.

Other Approaches. Model-fitting is a segmentation method that involves fitting a simple geometric shape to the locations of extracted image characteristics in an image, such as an ellipse or parabola. This technique is specific to the structure being segmented, although it is simple to use and can yield good results if the model is correct. Fitting spline curves or surfaces to the features is a more general approach. The fundamental challenge with model fitting is that image features must be retrieved first before fitting can begin. The watershed algorithm uses concepts from edge detection and mathematical morphology to partition images into homogeneous regions. The method can suffer from over segmentation, which occurs when the image is segmented into an unnecessarily large number of regions.

Conclusion

Image segmentation is the division of an image into its constituent homogenous sections with the goal of extracting data from the image's properties. As a result, good segmentation should result in zones where picture elements have uniform brightness, color, texture, and other attributes. Despite the fact that the image will be divided into parts, the significant changes within the regions should be visible visually. The quality of segmentation is measured by how similar the elements of the same region are and how distinct they are from the elements of different regions. The segmentation process can be classified into several categories depending on the segmentation parameter used, such as pixel intensity, homogeneity, discontinuity, cluster data, topology, and so on. Each method has its own set of benefits and drawbacks. The result achieved using one method may differ from the one obtained using another method. Methods that are tailored to specific applications can often outperform others, and choosing the right approach to a segmentation problem can be a difficult decision. In general, segmentation can be semi-interactive or completely automated. The segmentation algorithms that have been created fall into one of these categories. With the major challenge of segmentation's illposed nature, it's difficult to get a single solution for segmentation of a given image because interpretation differs from distinct methodologies. Manual picture segmentation can be error-prone in some circumstances (for example, seed selection), while completely automated approaches can produce incorrect results (for example, watershed segmentation), and interactive methods can be difficult and time-consuming in others. As a result, a single method for segmenting a wide range of images may be impractical. Prior knowledge about the image can improve outcomes and allow the user to choose the best approach for segmenting the image.

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