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Review of improved A.I. based Image Segmentation for medical diagnosis applications

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Abstract— Image segmentation is very important application in a biomedical diagnosis use image data analysis. In medical analysis the accuracy of image segmentation has a critical clinical requirement for the localization of body organs or pathologies in order to raise the quality of prediction of disease or infections. This paper covers review that includes several articles in which latest A.I biomedical image segmentation techniques are applied to different imaging color space models. This review article describes how various computer assisted diagnosis system works for achieving the goal of finding abnormal segments of body organs in biomedical images of the MRI, ultrasound etc. It has been observed that those segmentation approach are broadly giving accurate results in which the segmentation of the images is performed by defining an active shape model and then localization of potential area of interest using thresholding.

Keywords— Image processing, biomedical analysis, detection, pattern recognition

I. INTRODUCTION

The use of colour and texture information collectively has strong links with the human perception and in many practical scenarios the colour-alone or texture-alone image information is not sufficiently robust to accurately describe the image content. An example is provided by the segmentation of natural images that exhibit both colour and texture characteristics. This intuitive psychophysical observation prompted the computer vision researchers to investigate a large spectrum of mathematical models with the aim of sampling the local and global properties of these two fundamental image descriptors. Nonetheless, the robust integration of colour and texture attributes is far from a trivial objective and this is motivated, in part, by the difficulty in extracting precise colour and texture models that can locally adapt to the variations in the image content. In particular the segmentation of natural images proved to be a challenging task, since these images exhibit significant in homogeneities in colour and texture and in addition they are often characterised by a high degree of complexity, randomness and irregularity. Moreover, the strength of texture and colour attributes can vary considerably from image to image and complications added by the uneven illumination, image noise, perspective and scale distortions make the process of identifying the homogenous image regions extremely difficult. All these challenges attracted substantial interest from the vision researchers, as the robust integration of the colour and texture descriptors in the segmentation process has major implications in the development of higher-level image analysis tasks such as object recognition, scene understanding, image indexing and retrieval, etc.

Medical images play vital role in assisting health care providers to access patients for diagnosis and treatment. Studying medical images depends mainly on the visual interpretation of the radiologists. However, this consumes time and usually subjective, depending on the experience of the radiologist. Consequently the use of computer-aided systems becomes very necessary to overcome these limitations. Artificial Intelligence methods such as digital image processing when combined with others like machine learning, fuzzy logic and pattern recognition are so valuable in Image techniques can be grouped under a general framework; Image Engineering (IE). This is comprised of three layers: image processing (lower layer), image analysis (middle layer), and image understanding (high layer), as shown in Fig 1. Image segmentation is shown to be the first step and also one of the most critical tasks of image analysis. Its objective is that of extracting information (represented by data) from an image via image segmentation, object representation, and feature measurement, as shown in Fig 1. Result of segmentation; obviously have considerable influence over the accuracy of feature measurement [2]. The computerization of medical image segmentation plays an important role in medical imaging applications. It has found wide application in different areas such as diagnosis, localization of pathology, study of anatomical structure, treatment planning, and computer-integrated surgery. However, the variability and the complexity of the

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anatomical structures in the human body have resulted in medical image segmentation remaining a hard problem [3].

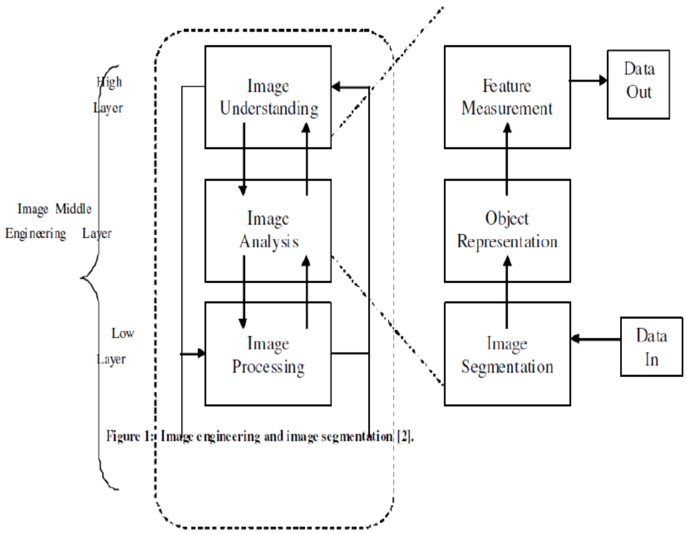


Figure 1: Image engineering and image segmentation [2].

Based on different technologies, image segmentation approaches are currently divided into following categories, based on two properties of image.

A. Detecting Discontinuities

It means to partition an image based on abrupt changes in intensity [1], this includes image segmentation algorithms like edge detection.

B. Detecting Similarities

It means to partition an image into regions that are similar according to a set of predefined criterion [1]; this includes image segmentation algorithms like Thresholding, region growing, region splitting and merging. Thresholding is a very common approach used for Region based segmentation where an image represented as groups of pixels with values greater or equal to the threshold and values less to threshold value.

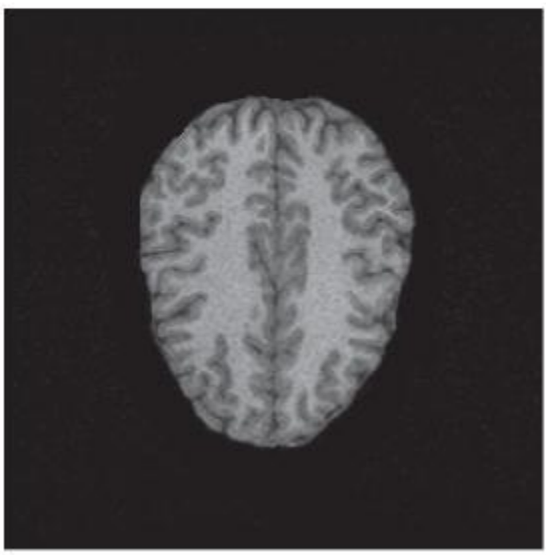
Clustering is also an approach for region segmentation where an image is partitioned into the sets or clusters of pixels having similarity in feature space. Region growing is another approach of region segmentation algorithms where assigned the adjacent pixels or regions to the same segment. There are three types of images as gray scale, hyper spectral and medical images.

2. Segmentation Techniques

Large complexity and variability of appearances and shapes of anatomical structures make medical image segmentation one of the most challenging and essential tasks in any CAD system. Due to diversity of objects-of-interest, image modalities, and CAD problems, no universal feature set and general segmentation technique exist. Some popular rule-based, statistical, atlas based, and deformable models based techniques, and their key strengths and weaknesses are outlined below.

A. Rule-Based Segmentation

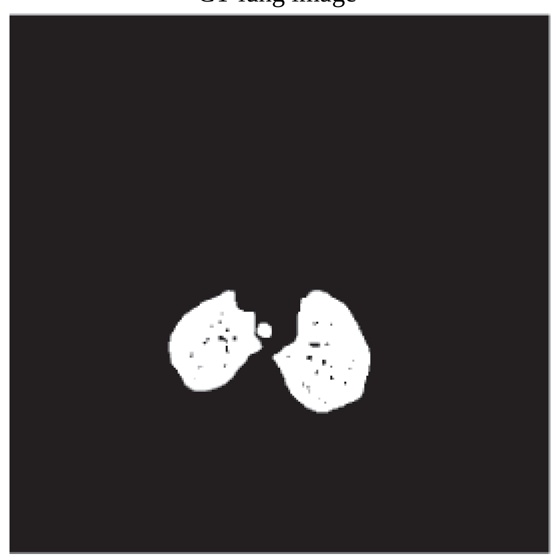
In this case, image features over an individual region comply with a set of heuristic rules. Simple and straightforward feature thresholding is widely used, due to its computational simplicity and speed, for fast initial segmentation or at intermediate stages of various segmentation scenarios, but usually it cannot stand alone for the final segmentation. The simplest thresholding divides an image into two regions related to a goal object and its background, respectively: e.g., an object label is assigned to each pixel or voxel if its intensity exceeds a certain threshold; otherwise, it is classified as the background. The threshold can be fixed through all the image (global thresholding) or vary according to the pixel/voxel location (adaptive, or local thresholding). Frequently, it is selected by statistical analysis of image intensities over the whole image or a certain vicinity of the pixel or voxel under consideration, e.g., peaks and valleys of the gray-level histogram, or by optimizing a certain image-dependent criterion, e.g., minimizing the cross-entropy between an input gray-level image and the output binary image [4]. Figure 1.8 illustrates the global-threshold-based segmentation. If the intensity distributions for the object and background totally or partially intersect, simple comparisons to a global threshold either fail or produce too inaccurate results. Moreover, the thresholding does not guarantee connectedness of the found objects, which is a basic requirement in many medical imaging and CAD applications. More details about these techniques can be found in [5]. Region-growing (also called region merging) techniques guarantee a connected region for each segmented object. After initial seeds are selected, their neighbors are added up, and the group continues to grow by including adjacent pixels/voxels that comply with a predefined criterion specifying the required properties of the regions. Segmentation results depend on the latter criterion and rules for selecting the seeds and specifying the neighbors. Figure 3 illustrates a simple region growing procedure. First, a binary image is produced by global thresholding of the initial gray-scale image. Then a seed is selected manually within the region of interest, and begins to grow by testing and adding the immediate eight neighbors having the same properties (the intensity below the threshold). The process is repeated for each added pixel until no more connected neighboring pixels have the same intensity. For textured images, more complex region-growing procedures are to be involved, e.g., using the first- and second-order statistics (e.g., mean and standard deviation) for the current region and the candidate intensity to decide whether the neighbor should be added to the region [6]. The process is repeated and the statistics are recomputed for each added pixel until no more pixels are accepted. Obviously, the region growing techniques are very sensitive to initialization and often need user assistance to select proper seed points. Region split-and-merge techniques partition an image initially into a number of regions and then iteratively merge and/or split the current regions in accord with a certain region homogeneity rule. Just as the region growing, the split-and-merge approach is also sensitive to the initialization. However, its known applications to medical image segmentation include large brain lesions [7], cavity deletion [8], retinal blood vessels [9], and pulmonary nodules [10]. Additional information about the split-and-merge and region growing segmentation can be found in [11].



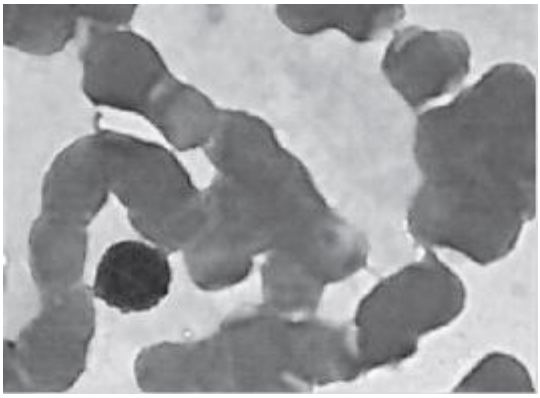
Brain MRI

White matter map (the threshold 128)

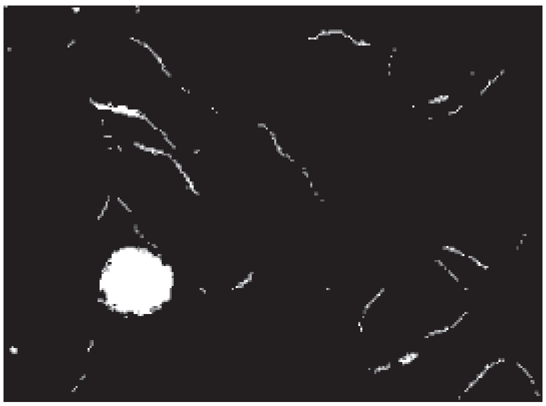
CT lung image



Lung tissue map (the threshol 135)

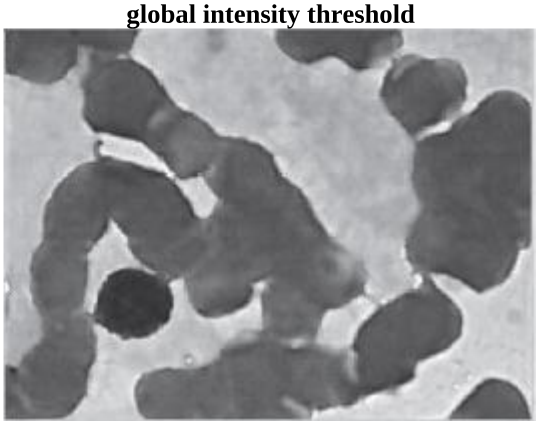


Cell image

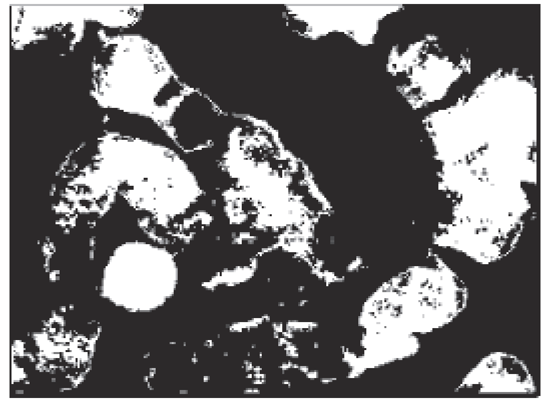


Cell map (the threshold 65)

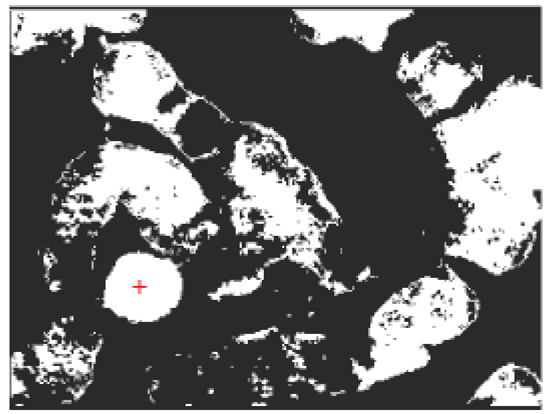
Fig. 2. Segmentation of anatomical structures with a global intensity threshold



Cell Image



Global intensity threshold 102



Manually selected seed (in red)

Region grown from the selected seed

Fig. 3. Segmentation by thresholding followed by region growing

B. Segmentation by Optimal Statistical Inference:

Statistical image segmentation involves parametric or nonparametric probability models of appearance and shape of goal objects and optimal, e.g., Bayesian or maximum likelihood inference [12]. Popular nonparametric probability density models are built using the k-nearest neighbor and Parzen-window estimators [13]. Popular parametric models exploit tractable analytical representations that allow for analytical or computationally feasible numerical parameter learning. In particular, the maximum likelihood estimates (MLE) of parameters of a Gaussian model are analytical, namely, the mean and the covariance matrix for a given set of training samples, while parameters of a Gaussian mixture model (the means, covariance matrices, and prior probabilities of the Gaussian components) are learned in part numerically and in part analytically with expectation-maximization (EM) techniques [14].

C. Atlas Based Segmentation

The use of anatomical atlases as reference images to guide segmentation of new images is very popular in different medical applications, e.g., for segmenting brain and its internal structures or segmenting pathological lungs, lung lobes, heart and aorta, and internal abdominal organs [12]. The atlas typically depicts prototypical locations and shapes of anatomical structures together with their spatial relations [15]. All the known atlas-based methods can be classified into single and multi atlas-based segmentation.

Single atlas-based segmentation uses an atlas constructed from one or more labeled segmented images. Once the atlas is created, it is registered to the target image, and the goal region map is obtained by so called label propagation that transfers the labels from the atlas back to the image using the same geometric mapping as the registration. Obviously, the segmentation accuracy depends on the registration (if the latter fails, so does the segmentation). The registration always involves time consuming and complex local deformations. Also, the segmentation is affected by the ability of the atlas to represent the whole population of images under consideration.

A single image to construct the atlas can be selected randomly, or by visual inspection based on practical criteria, or made artificially [16]. If the atlas is constructed from several images, one image can be selected as a reference and all other images are registered to it. To increase the signal-to-noise ratio, all the registered images are averaged, and the segmented average image is used as the atlas [17]. Alternatively, the atlas can be built by transforming the reference to the average image and segmenting the transformed reference [18]. Probabilistic atlases built by averaging the transformed images and analyzing the corresponding labels [19] provide different weights of each pixel. However, an average atlas does not handle elastic deformations of internal structures during the registration process. To overcome this problem, Leemput [20] proposed a mesh-based atlas representation instead of the average atlas. Also, an iterative atlas generation uses the output of each iteration as the input of the next iteration [15].

Multi atlas-based segmentation registers many independently built atlases to a target image and then combines their segmentation labels. The underlying idea is that fusion of multiple independent classifiers might produce better classification [21]. There exist different ways for segmenting a particular target image, e.g., to select all the atlases or only their subset as well as to choose one or another strategy of combining the selected atlases to produce the goal region map. The pre or postregistration selection of atlases can be based on certain matching criteria such as the mutual information or the degree of deformation of the object of interest (obviously, the atlases of the highest local mutual information or the least object deformation are preferable).

Popular strategies of combining the selected atlases to segment the target image include decision fusion (also called majority voting, majority rule, or label voting). In this strategy, the label of each pixel or voxel is selected as the label that most of the segmentations agree on [22]. Another strategy, called simultaneous truth and performance level estimation (STAPLE), evaluates the performance of each classifier iteratively, weighs the corresponding segmentation accordingly, and uses the EM approach to find the best final segmentation [23]. Isgum et al. [16] combined the propagated labels by spatially variant decision fusion weights derived from the local assessment of the registration accuracy, and Rohlfing and Maurer [24] proposed a shape-based averaging strategy based on the Euclidean distance map to perform the combining.

D. Segmentation with Deformable Models

Since the seminal paper by Kass et al. [25], deformable models became a dominant technique and gave rise to one of the most dynamic and successful areas in image segmentation, edge detection, shape modeling, and tracking of medical image structures. These techniques have quickly gained widespread popularity due to superiority over other segmentation techniques. In particular, these models end up with a continuous boundary of an object of interest in spite of possible large shape variations, image noise and inhomogeneities, and discontinuous object boundaries due to occlusions. In addition, they incorporate both the shapes and appearances of the objects of interest as their most significant discriminative features, and can be aided by interactions with the users. A deformable or active model is a curve in a 2-D digital image or a surface in a 3-D image that evolves to outline a goal object. Its evolution is guided by internal and external forces, which are defined so that the deformable model will eventually conform to the object boundary. The internal forces, coming from the curve/surface itself, are designed to keep the evolved curve smooth and unified. The external forces, depending on the image, propagate the evolution towards the object boundary. By representation and implementation, the deformable models are divided into two broad classes: parametric [26] and geometric [27].

II. CONCLUSION

This work comprises review of several segmentation methods applied for biomedical image segmentation. It has been observed that segmentation these techniques consist of pattern recognition in the images using an active shape model and then localization of potential lesions using thresholding. The second methods of segmentation are helpful in cardiac images MRI or ultrasound images. The segmentation is performed by using a region based snake where the data term is driven by virtual image forces derived from the image intensities. To overcome problems with the cardiac valve opening and closing during the cardiac cycle, we annotate two anchor points, one on each side of the valve. This method shows promising results. In some paper it is observed that methods are developed with objective of measuring the abnormality in shape of the organs achieved using the shortest path algorithm. The measurement consists of analysis of how much it deviates from a normal one. It can be concluded that the segmentation quality can be further improved by applying a two-stage method processing of both textured and non-textured.

First stage calculates textured features from the bands coefficients of the dual-tree wavelet transform of image. Thereafter filtering should be applied to minimize the ambiguities of texture regions at the boundaries of the image objects. The calculated texture feature can be used to find the space based gradient function thus the segmented regions obtained by transformation can be grouped to meaningful region of similar features by using spectral clustering technique by using the weighted mean based cost function for region partitioning.

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