The Status Quo of Artificial Intelligence Methods in Automatic Medical Image Segmentation

Maryam Rastgarpour and Jamshid Shanbehzadeh

***Abstract*—Image understanding needs to image analysis accurately in medical image engineering. Since segmentation is an effective and fundamental step in the medical image analysis (MIA), many efforts have being done to increase accuracy. One of the promising and fruitful efforts is using the artificial intelligence (AI) methods. This paper proposes a new notation for medical image segmentation (MIS) namely the status quo of AI techniques used to automate MIS. It considers four categories for segmentation methods based on applied AI techniques. These methods can decrease the human intervention gradually as well as showing this development; it tries to full automated segmentation. Each category facilitates the higher level of AI techniques than the previous one does. They are respectively based on Image Processing techniques, Hybrid AI methods, Expert systems development and ultimately registration-based in the multispectral and multi modal imaging.**

***Index Terms*—Artificial intelligence methods, medical imaging, image segmentation, medical image analysis.**

I. Introduction

Processing and analysis of health information is a conventional method in care and treatment services. So applying the AI techniques in medicine is a new branch of research. It is rapidly expanding in storage, data retrieval and optimal use of information analysis for decision making in problem solving and improving healthcare systems and effective treatment [1].

Automatic analysis of medical images is significant and beneficial for computed diagnosis, computed surgery, computed therapy, medical studying and research in the field of anatomy [2]. Algorithms of automatic MIA can improve efficiency and its understanding of them [3]. The correct identification of biological features of ROIs has an important role in their accurate analysis. Many efforts have being done to increase efficiency. One of the promising and fruitful efforts is using the AI methods such as digital image processing and also combining with other methods like machine learning, fuzzy logic and pattern recognition [4].

In MIA, segmentation is so crucial for more concentrations in later steps namely feature extraction, image measurement and ROI representation. Furthermore, segmentation of the ROI should be done correctly to obtain some determinant features of disease or subsequent lesion.

But this operation is very difficult. It is often done by a human manually. Unfortunately this manual segmentation is too time-consuming. So segmentation of many scans is not possible. Additionally the number of images for analyzing is growing strongly due to technological advances. Hence, manual segmentation is not feasible in clinical operations as well as human interpretation may not be produced suitable. Thus intelligent tools are so essential to segment automatically. For more information about current methods of Medical Image Segmentation (MIS) and some categorizations of them please refer to [4]-[18].

The rest of this paper is organized as follows. Section II summarizes medical image engineering. Section III explains medical image analysis too. Then the focus on the segmentation as a crucial step in the MIA as well as the mathematical definition of MIS is presented in section IV. The status quo of AI techniques to automate MIS is described in section V. Finally the paper concludes in section VI.

II. Medical Image Engineering

Similar to general schema for image engineering [5] and [6], Medical image engineering contains three main steps based on processing level:

Low level processing (medical image processing): contains primitive operations such as noise reduction, edge detection, contrast enhancement and sharpening of medical images. The inputs and outputs are medical images.

Middle level processing (medical image analysis): involves tasks such as segmentation (partitioning an image into ROIs like tumors and lesions), description of those objects to reduce them into a suitable form to process and classify (recognize) individual objects by computer. The inputs are images generally and outputs are the extracted attributes from those images like edges, contours, and the identity of individual objects.

High level processing (medical image understanding): includes "Making Sense" of an ensemble of recognized objects in image analysis and carrying out the cognitive functions normally associated with vision which is so helpful for clinicians.

In this paper, Segmentation in the middle level of medical image engineering, i.e. MIA, is concentrated to perform the interpretation and analysis of the disease accurately. So in the following, medical image analysis would be described in detail.

III. Medical Image Analysis

Quantitative analysis of medical images, namely the

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measurement of volumes, needs to describe anatomy structures. This information is obtained by MIA. Fig. 1 shows the general scheme of MIA system. In this scheme, first an image of interested region is acquired by the proper imaging device like MRI for soft tissues then it would be processed by the image processing unit facilitated by MIA tools. MIS, ROI representation, feature extraction and maybe feature selection are achieved in MIA tools. Lastly the data out is injected to high level processing in MIE.

Automatic analysis of medical images needs many image processing techniques and also preprocessing operations like noise removal, image enhancement, and edge detection and so on. Thus after finishing these preliminary steps, the image is ready to be analyzed. The preprocessed image is imported to a MIA system. Then mining ROI from the image is done in the segmentation phase by combination of intelligent methods which is explained in detail in the following sections. Afterward ROI representation, description and measurement are carried out. Moreover features extraction (and probably features selection especially in multi modal and multi spectral imaging) is performed to identify and recognize the ROI which may be a tumor, lesion, and abnormality and so on.

IV. Medical Image Segmentation

Accurate diagnosis and treatment of diseases is vital. They make the automatic MIA complicated. Furthermore the researches have shown that incorrect analysis of images is often the result of improper segmentation, because the segmentation result effects on the later steps namely ROI representation and feature extraction in MIA. So to obtain some determinant features of disease or subsequent lesion in MIA, segmentation of the ROIs should be done correctly. Therefore a proper segmentation method is critical [1] - [4], [7], and [19]-[21].

In medical applications, segmentation identifies the boundaries of ROIs including tumors, lesions, abnormalities, the bony structures, blood vessels, brain parts, breast calcification, prostate, iris [22], abdomen [23], pulmonary fissure, cartilage knee and etc. Two samples of segmentation are shown in Fig. 2. Mathematical definition of segmentation is in the following subsection.

Disease type and image features determine the proper method of segmentation. It causes segmentation method to be dependent on modality and dimension of imaging. There are many literatures in the field of MIS such as [4], [7]-[19].

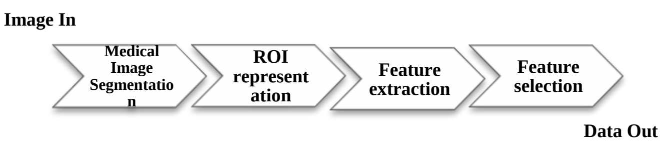
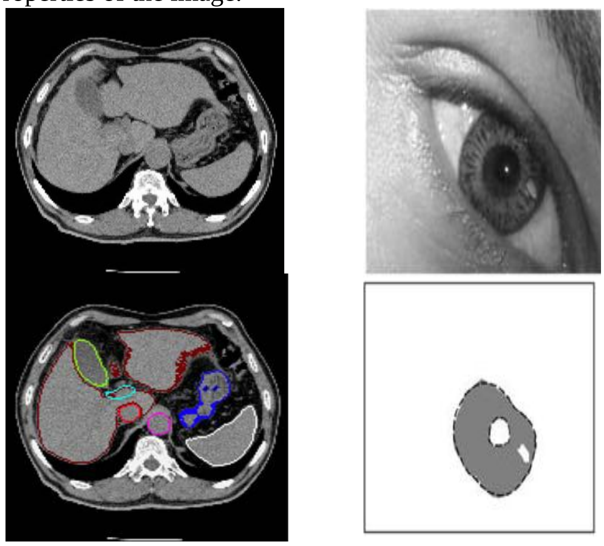


Fig. 1. General scheme for medical image analysis system

A. Mathematical Definition in Mis

A general definition of MIS [24] is as follows. This definition uses a homogeneity predicate P () that helps formalizing the notion of homogeneity in an image: a region R is homogeneous if and only if P(R) = True. Therefore, the homogeneity can be defined in infinity of different ways: on the grey levels, on the textures or even on non-obvious properties of the image.



a) Abdominal segmentation [22] (courtesy of Prof. Hugo Proenca) b) Iris segmentation [23]

Fig. 2. Two samples of segmentations – the original images are on top and the segmentation results are on bottom

Definition of MIS: Assume I be the input image and the set of pixels and also define a homogeneity predicate, i.e. P (), on the clusters of connected pixels. So the following equations should be satisfied for an accurate segmentation:

A segmentation S of I is a partitioning set of image regions $\{R_1, R_2, \ldots, R_n\}$ such that the union of all the regions covers the whole image I and all the obtained regions are distinct:

$$\bigcup_{i=1}^{n} R_i = I \qquad and \qquad R_i \cap R_j = \emptyset \qquad \forall i \neq j \tag{1}$$

The homogeneity predicate, P(), is valid on every region:

$$P(R_i) = True \qquad \forall i \tag{2}$$

Two adjacent regions must be distinct regarding the homogeneity predicate. In other words, the union of two adjacent regions cannot satisfy the homogeneity predicate:

$$P(R_i \cup R_j) = False \qquad \forall\, R_i\ adjacent\ to\ R_j \tag{3}$$

The homogeneity predicate is valid on any sub-region of a region where it is verified:

$$(R_i \subset R_j) \wedge (R_i \neq \emptyset) \wedge (P(R_j) = True) \Rightarrow (P(R_i) = true) \tag{4}$$

V. AI in Medical Image Segmentation

Accurate analysis of medical image needs to a novel anatomical or functional insight. It is because of some reasons include in improving in interpretation of test data, doing tasks as full or semi-automated, increasing accuracy and also providing searching in new modality of imaging. This insight is provided by image processing techniques and other AI methods [25].

Recent advances in AI methods such as image processing operators, adaptive learning and knowledge-based systems enhance diagnosis information for computed tomography and therapy in MIA. Since desired information about biological objects is related to fundamental features, it's necessary to apply the image processing methods for segmentation and visualization of radiological interested facts in medical images.

It's clear that the image processing techniques can't process the medical image accurately alone. So the devices of MIA are facilitated by some AI techniques to increase accuracy. Consequently radiologists can diagnosis cancers, heart disease, infectious diseases and muscular skeletal disorders simpler and more accurate by using of special and attentive devices for interpretation the medical images [25].

The segmentation methods depend on modality and dimension of imaging. It is because of segmentation dependency on factors like disease type and image features. Likewise, segmentation needs the image interpretation because application-based. So these dependencies result in a significant growth of literatures annually [19, 26].

A few classifications of literature [11] and [27] has been organized in different categories based on amount of human intervention, application of model and prior knowledge, evaluation and validation of the segmentation method, using local or general data, dimension and modality of imaging, disease features, AI technique based and non- AI technique based [28], and so on. None of available classification leads to a crisp partition of them [2]. Some of the categorization is summarized as follows:

In [7] the segmentation methods of MRI images have been looked over in aspect of single or multiple spectral and also supervised or unsupervised until 1995. Withey[11], [20] considered three generation to classify the literatures, they are respectively application of image processing methods; optimization methods and uncertainty models; and finally the higher level of knowledge like prior information, some rules defined by experts and models of ROI form. Pan [18] classified the segmentation methods in four groups including interactive thresholding, edge detection, regions split and merge, and finally hybrid methods. Dellepiane [27] classified the literatures based on a tree rooted that partitioned algorithms based on directorial parameters to their goal. He deliberated density, topology, and geometry as the basis of the main groups.

Accordingly, one can categorize the available segmentation methods in the following four categories based on the applied AI methods [25]:

The methods based on *image processing operators* – i.e. they have a *low level processing* such as thresholding, edge detection, and region growing and so on (e.g. [15], [18] and [29]).

Hybrid methods, i.e. application of some other *intelligent methods* in category 1 – to increase the accuracy of those methods in the category 1, one can combine some AI method like pattern recognition and machine learning algorithms (i.e., c-means clustering, artificial neural networks, active contours, level set, hidden markov models and so on) with image processing operators, for example [30]-[32]. These methods are progressing to semi-automatic.

Expert system of category 2 – Considering an expert system for the methods in category 2 with the goal of progress toward full automatic segmentation which is using experts' knowledge in the form of rules, models [33] and atlases [34].

Using *multispectral and multimodal images* in category 3. Segmentation method is based on registration in this category. These methods use more several features of multiple modalities to increase accuracy in comprising with the other categories [3], [9], [35]-[37].

Not only each category gets more complex and accurate gradually but also human intervention would be decreased in comparison with the previous categories. Region identification, boundary following, and pixel classification can link the methods in each set to those of previous categories [19].

Most traditional segmentation techniques use images that represent only one image type, for example, MR or CT. But the segmentation method in category 4 uses multiple images of an organ to have several features by using variant modalities such as CT, MR, PET, ultrasound, or collection of images over time. These features make segmentation more accurate. These methods are called *multispectral* or *multi-modal*. There are many intelligent methods applied in this category such as k-means, fuzzy c-means, expectation maximization and adaptive template moderated spatially varying statistical classification etc. and need to image registered properly. More information about this categorization presented in [25].

VI. Conclusion

This paper tried to give precise information about image segmentation in medical applications. It summarized medical image engineering first and then explained MIA. It focused on segmentation as a crucial step in the MIA then. The status quo of AI techniques to automate MIS was described by categorization of the current methods in four categories. They are respectively based on *Image Processing techniques*, *Hybrid AI methods*, *expert systems* and *registration*.

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