Image Segmentation: Computational Approaches for Medical Images

Rupanka Bhuyan
Department of IT & Mathematics, Icfai University Nagaland,
6th Mile, Sovima,
Dimapur, Nagaland - 797112

Samarjeet Borah
Department of Computer Science and Engineering,
Sikkim Manipal Institute of Technology,
Majitar, Rangpo,
East Sikkim - 737132

ABSTRACT
Image segmentation is a prominent problem of research in the field of computer science and an evolving concept. No perfect solution to this problem has been found till date. This paper presents some of the fundamental concepts in image segmentation and lay special emphasis on images used in the medical domain. Certain commonly found problems which are inherent in medical images are also discussed. Various approaches for segmenting medical images and related issues have been discussed. Observations are being made on the approaches, issues and their relative merits and demerits.

General Terms
Image Segmentation, Medical Image Processing.

Keywords
Image Segmentation, MRI, CT, thresholding, Region-Growing, Classifiers, Clustering, MRF Models, ANN, Atlas Guided Methods, Level Set Models, Deformable Models.

1. INTRODUCTION
The process of image segmentation is applied on grayscale or color digital images to generate compact, non-overlapping, discrete and semantically meaningful partitions out of the image [1][2][3]. Each such partition is made up of pixel sets. Generally, texture or pixel intensity [4][5] may be a characteristic on the basis of which this partitioning is carried out. Human beings can differentiate between thousands of color shades and intensities and around twenty shades of gray and can easily segment any given image. In contrast to this, achieving the same feat still remains a big challenge when it comes to the case of even the latest computers of today [6]. It is to be noted that, the condition or criterion for a “correct or good” segmentation could not yet be decided upon by the fraternity of computer vision experts [7].

1.1 Applications of Image Segmentation
There are many emerging areas where image segmentation techniques are being applied but its most common applications can be found in the fields of (1) fingerprint recognition, (2) object detection, (3) medical imaging, (4) content-based image retrieval, (5) face detection, (5) pedestrian detection, and (6) video surveillance. In many of these applications, it is used as an image preprocessing step [8] before executing higher level activities such as – (1) image analysis, (2) image enhancement, (3) image classification, (4) image recognition, and (5) semantic interpretation of images, etc. This type of preprocessing is used to improve the computational efficiency of the mentioned higher level activities.

1.2 How this paper is organized
This paper is organized as follows. Some basic concepts used in the context of medical images are provided in section 2. In section 3, literature review is done on the various methods proposed for (medical) image segmentation, the challenges, the validation techniques and about available resources in this field. Our observations and conclusions are furnished in section 4.

2. BASIC CONCEPTS
In the context of medical images available and commonly used for segmentation processes, some of the basic concepts in that domain are highlighted below.

2.1 Digital Images
A digital image is basically a collection of measurements in a 2 or 3 dimensional space. A scalar image contains one measurement at each of its locations, while a vector or multi-channel image contains more than one measurement at each of its locations. In 2 dimensional images this location is called a *pixel* while, in a 3 dimensional image the same is known as a *voxel*.

2.2 Image Type
Grayscale (also called Monochrome) digital images are devoid of any information about color and represent the entire image using different shades of gray. Color images represent an image using few hundreds of shades of different colors. It is worth mentioning that, a majority of the color image segmentation techniques are based upon the grayscale segmentation based techniques.

2.3 Modality
Some of the common modalities for performing medical imaging are – (1) Magnetic Resonance Imaging (MRI) which is the most commonly used radio imaging technique [9] carried out to diagnose and monitor the treatment of anatomical parts such as - brain, liver and chest by acquiring their structural details, (2) Computed Tomography (CT) imaging [10] procedure is used incorporating X-rays to obtain structural and functional information about the human body such as - brain, liver, chest, abdomen and pelvis, spine, etc., (3) Ultrasound which is one of the popular methods used for motion estimation tasks, and (4) Positron Emission Tomography (PET) which is an imaging technique used to

acquire images of physiologic functions by using nuclear medicine [11].

2.4 Color Spaces

Color spaces are abstract mathematical models which are used to precisely define and represent color in digital images by using numbers in a 3 dimensional coordinate system. The coordinates may represent values of parameters like – (1) red, green and blue, or (2) hue, lightness and saturation, or other values pertinent to the color model being used. Some commonly used color spaces are (1) RGB, (2) nRGB, (3) HSI, (4) CIE L*u*v*, (5) YIQ, and (6) YUV [12]. All these schemes represent color values in different ways. However, Chang et al. [13] claim that HSI color model has good capability of representing the colors of human perception especially good for images having non-uniform illumination, while CIE is efficient in measurement of small color differences. Again, certain models such as the ACRM (Approximate Color-Reflectance Model) is good for eliminating effects such as – shadows, highlights in the original images. Other than using any one of the color spaces, a digital image also can migrate from one space to another. Again, in case of certain segmentation methods, using one color space over another may produce different segmentation results.

3. MEDICAL IMAGES

MRI, X-ray projection radiography, CT and other such imaging modalities mentioned in section 2.3 are very commonly available non-invasive procedures used nowadays to produce fast mapping of the human anatomy. In the application areas such as (1) computer integrated surgery, (2) diagnosis, (3) study of anatomical structure, (4) localization of pathology, (5) quantification of tissue volumes, etc. the use of image segmentation has become very valuable and has received considerable importance today. The primary objective of image segmentation of medical images is to discover previously unseen or un-noticed information from an originally inputted image such as an MRI, or Ultrasound, etc. The output of this segmentation may result in anatomical areas consisting of heart, liver, brain and other related parts.

3.1 Problems in Medical Images

There are some inherent problems common in medical images. They are - (1) the partial volume effect – where a single pixel volume is comprised of a mix of different tissue classes, (2) intensity nonuniformity - where there is variation in the intensity level of a single tissue class, and (3) noise (because of sensors and electronic systems) - which can alter the intensity of a pixel resulting in uncertain classification [14][15].

3.2 Segmentation Approaches

A lot of work has been done in the area of image segmentation for over the past four decades or so. Discussed below are some of the most common segmentation approaches which have been proposed during the last 22 years.

3.2.1 Region-Growing

Region-Growing methods work by manual selection of an initial pixel (*seed*) by an operator (as shown below in Figure 1) and extraction of pixels with the same intensity. Seeds are to be planted for each region to be extracted. Commonly these type of methods suffer from problems like partial volume effect and noise. But, J. K. Udupa et. al. have proposed a 'fuzzy variant' of the region-growing method in [16] and J. F. Mangin et. al. have proposed one using 'homotopic technique' in [17]. Both these variants minimize the drawbacks of sensitivity-to-noise and partial-volume-effects.

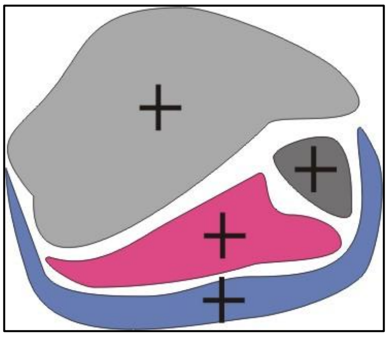

Figure 1: Region-Growing

3.2.2 Level Set Methods

This topology independent shape modeling scheme can be applied to images containing multiple objects of interest; wherein an object can have arbitrary shape and significant protrusions. R. Malladi et. al. applies Level Set Methods for medical image segmentation in [18]. A. Ahirwar in [19] states that these methods are particularly appropriate in handling features such as cavities, convolution, etc. Acceptable outcomes by these methods are subject to symmetrical placement of initially inputted curves w.r.t. the object boundary.

3.2.3 Classifiers

In [20], J. C. Bezdek et. al. and R. J. Schalkoff et. al. in [21] have reviewed classifiers which are supervised pattern recognition techniques. New data are classified based on manually segmented training data. There can be parametric (eg. kNN, Parzen Window) or non-parametric (eg. Bayes or Maximum Likelihood) classifiers. The result of classification is a feature space which is derived by using known labels on an input image.

3.2.4 Clustering

Clustering techniques are used for mining data to discover useful patterns. Clustering methods produce distinctly different groups out of data objects from a given data set. Each of these groups contains objects which are similar to other objects in the same group and are dissimilar to objects in other groups. H. J. Kamber discusses unsupervised methods like clustering in [22]. Again, there are different types of clustering techniques. Some clustering techniques exist for segmentation of medical images. While, J. C. Bezdek et. al. in [20] and J. C. Dunn et. al. in [23] discusses about fuzzy c-means, G. B. Coleman in [24] et. al. elaborates on k-means. In reference [11], T. Lei et. al. and separately Z. Liang et. al. in [25] reviews expectation-maximization (EM). Advantages of the clustering methods are speed and lack of requirement for any training data. However, sensitivity to noise and affectability by inhomogeneities add up as drawbacks. Also, spatial modeling is lacking in these methods.

3.2.5 Thresholding

Thresholding techniques were one of the earlier techniques used in the area of image segmentation. P. K. Sahoo et. al. in [26], discusses about the *thresholding* technique. Thresholding techniques work by determining one or more threshold value(s) for the pixel intensity of a digital image. Pixels satisfying this criterion are put together into one group and those not satisfying the same are put into another. More than one group are also possible with multi-thresholds as shown below in Figure 2. In reference [27] D. L. Pham et. al. states that this partitioning can be done automatically or interactively. Basic thresholding methods can produce only two classes. Thresholding methods are simple, fast and are appropriate for segmenting images with contrasting intensities. However, the technique is highly sensitive to noise and intensity homogeneities. Moreover, the spatial characteristics of an image are not considered by this technique.

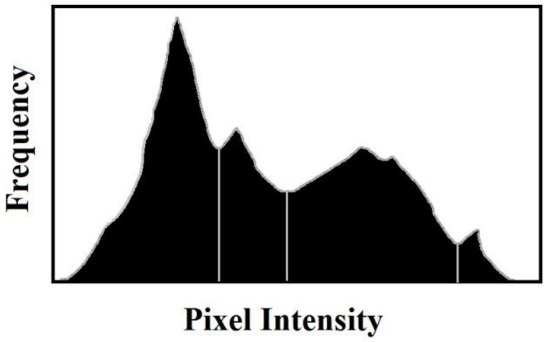

Figure 1: Thresholding

3.2.6 *Artificial Neural Networks / SOM*

Kohonen introduced the concept of Self Organizing Maps (SOMs) or Self Organizing Feature Maps (SOFMs) which are a special type of Artificial Neural Network (ANN) in [28]. In reference [29], J. W. Clark and S. Haykin in [30] define ANNs to be made up of nodes connected together. ANNs simulate the concept biological learning virtually. Multi-dimensional feature spaces can be represented intelligently in lower dimensions using SOMs. SOM based methods can be both supervised and unsupervised. H. Y. Huang et. al. proposed a two stage method for image segmentation which is one of the initial works in the area of SOM based methods in [31]. Some other methods similar to this one were also introduced. Later, in [32] D. E. Ilea et. al. proposed a completely automatic adaptive unsupervised segmentation algorithm. One advantage of SOMs is that they can incorporate spatial information with ease. To exploit the full potential of ANN based methods, parallel computers are required but, practically in majority of the cases this is close to impossible.

3.2.7 *Markov Random Field Models*

S. Z. Li explores the application of Markov Random Field (MRF) models in image segmentation in [33]. MRF is a statistical model that can be used within segmentation techniques like clustering. MRF can model spatial interactions between pixels. An advantage of the model is robustness to noise. The challenging issues in MRF based models are - (a) selection of proper parameters which control the strength of the spatial interactions, and (b) computational intensiveness.

3.2.8 *Atlas Guided Methods*

D. L. Pham in [27] et. al. and separately A. Ahirwar in [19] discusses about Atlas Guided Methods which are similar to classifiers. Prior compilation is done for an anatomy that needs to be segmented. To segment new images, this atlas is used as a reference frame. Between the pre-segmented image and the new image, one-to-one mapping (atlas warping) is carried out. A disadvantage with these types of methods is anatomical variability because of which accurate segmentation becomes difficult for complex images.

3.2.9 *Deformable Models*

Deformable models combine concepts from the fields of physics, geometry and approximation theory and have been used to produce segmentation of (1) bones in CT images, (2) cardiac images and (3) ultrasound. These methods exhibit robustness to both *noise* and *spurious edges*. Several segmentation methods based on the deformable model approach have been proposed over the years. McInerney [34] introduces the use of 'deformable organisms' which combines concepts from the field of artificial life with deformable model methodologies. Prasad et. al. [35] introduces a technique using these deformable organisms to segment brain MRI images. Among the recent works in this area of approach, Gopal et. al. [36] proposes a variant which incorporates statistical and deterministic deformable models to automatically segment cardiac MR images.

3.3 Validation Methods for Segmentation

Ill-posed due to its particular nature, the problem of image segmentation does not have any proper rule for validation of the obtained segmentation results. Most of the benchmarking databases containing segmented images (for validation purposes) are created manually by the help of human operators. Consequently, manually segmented results for the same image may vary from one human operator to another as the psychophysical perception from person to person varies. In case of brain scan segmentation results the comparison is usually done against the manually obtained results or, by using either physical phantoms [11] or computational phantoms [37][38].

3.4 Resources

Tools for both image segmentation and validation are available for academic, commercial and non-commercial purposes. Databases for validation of medical image segmentation can be found at [39], [40], and [41]. Some software tools for image segmentation can be found at [42], [43], and [44]. Open source software tools for image segmentation are also available as listed at [43], [45] and [46]. This list is not all inclusive of all the tools and databases available.

4. CONCLUSIONS

Firstly, it is observed that during the last four decades many algorithms have been proposed for the image segmentation problem. Algorithms developed during the last twenty years have used approaches involving - clustering, neural networks, fuzzy methods, level-set, thresholding, atlas-based, deformable models, etc. to name a few. Both supervised and unsupervised techniques have been in existence. No general approach in particular seems to solve the problem of segmentation and all the approaches are very subjective in nature. Algorithms using multiple methods such as clustering with Markov Random Field model, or Neural Networks or, even variants of the Clustering approach seem to be relatively more promising than the others. Among the clustering based methods, mostly K-means clustering and its variants have been used. One observation is that, not much exploration has been done using other unsupervised techniques such as density based clustering.

Secondly, there is a need to standardize the benchmarks available for validation of segmentation techniques. Or whenever a benchmark is created it should be based on more solid foundations.

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