An Investigation of Challenges in Automatic Segmentation of Medical Images

Sami Ur Rahman, Hussain Rahman, Fakhrud Din, Sehat Ullah, and Aziz Uddin

***Abstract* — Automatic medical image segmentation is an emerging field with upcoming new techniques that revolutionized how we view functional and pathological events in the body. Medical image segmentation is a very challenging problem and there is no standard segmentation technique that can automatically segment all types of three-dimensional medical images. Doctors and clinicians still prefer manual segmentation due to unreliability and unavailability of standard automatic segmentation techniques. Most of the segmentation algorithms are semi-automatic that require user interaction and are difficult for use in practical applications. Some of the algorithms that are automatic require very high resolution of images for segmentation. Moreover, segmentation algorithms for medical images are application specific and the algorithms developed for one application may not work for other type of application. There are a number of factors such as image noise, anatomy variation, disease type, intensity homogeneity, non-uniform object texture, image content, occlusion, input nature and special characteristics of image continuity that make the process of automatic segmentation more difficult and challenging. In this paper, we have categorized these challenges and have described their effects on commonly used segmentation algorithms using the criterion functions input type, dimensionality, anatomy variation, parameter tuning and need of user interaction.**

***Index Terms* — Automatic segmentation, human anatomy, image artifacts, image modalities, region of interest (ROI).**

I. INTRODUCTION

Image segmentation is a very important step in image analysis and computer vision [1]. Segmentation of medical images is the process of delineating anatomical structures of human body that helps the clinicians in disease diagnosis, treatment planning, detection of abnormalities, and analysis of anatomical objects [2, 3, 4, 5, 6]. Automatic medical image segmentation has a key role in various medical applications such as:

- Detection and measurement of tissue deformities
- Diagnostic radiology
- Recognition tasks such as iris, fingerprint and face recognition
- Registration of two and three dimensional image data
- Anatomical research on regular body structure
- Tumor and other pathologies localization
- Machine vision
- Disease progress detection
- Virtual reality and simulation
- Learning prior knowledge about body structures
- Classification, simplification, verification, visualization and extraction of region of interest (ROI) etc.

In the field of medical imaging, a large number of approaches such as thresholding, region growing, edge detection, morphological methods, neural networks, template matching and many more complex approaches [7] have been used but a standard automatic algorithm that can segment every type of image data is still awaiting. Various factors make the process of automatic segmentation more difficult.

Representation of domain knowledge about human anatomy in a computer system is very challenging. It is very challenging to define ROI in an image due to its size, shape and resolution. The second difficulty comes from the intrinsic properties of imaging systems. Missing information, homogeneity and low contrast of the image makes segmentation very difficult. Third challenge is the variation of anatomy between two different individuals. There exists a large difference in the same organ in different humans. The fourth challenge is the shape of vessels and other anatomic structures inside a human body that are not only complex but also highly variable. For each object, a different technique is needed to identify and separate it from other objects in the same image.

With rapid improvement of technology, increase occurs in size, resolution and dimension of medical images. An algorithm for a low dimension may not work with high dimension. Moreover, noise is present in most of the medical images. Filters are used to overcome this problem but useful information and details about the structures may lost by applying such type of operations. Similarly, the nature and type of input image affect the performance of an automatic segmentation algorithm. Algorithms produce different results due to change in parameters of a single object. Another complication that arises is the communication between patient-centered medical world and computer centered technical world that makes the research process more difficult. Due to all these challenges, the development of a universal standard algorithm is awaiting.

In this paper, there are three sections. In first section, the different types of commonly used segmentation techniques are shortly described with its advantages and limitations. In the second section, state of the art automatic segmentation algorithms are experimentally tested on real medical images to discover the challenges that affect the performance. Finally, the challenges with automatic segmentation are classified under four categories (Fig 1); imaging system related, patient related, image processing related and application related challenges.

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Existing methods for segmentation can be categorized into manual, semi-automatic and automatic segmentation techniques [8]. The classification is based on level of user interaction, application domain, user control and other specific factors. Manual segmentation is used to delineate a desired region from the image accurately. Doctors and clinicians prefer manual segmentation for medical applications due to unavailability of reliable automatic and semi-automatic techniques. However, there are some problems with manual segmentation such as:

- Manual segmentation is very time consuming and a volume image with a series of 100-500 slices takes more than an hour.
- Contouring of multiple axial images is very laborious.
- Brightness and contrast of display screen affect the segmentation results.
- Segmentation results are highly variable.
- Require experts for segmentation.

Semi-automatic segmentation is an interactive type of segmentation that requires the seed point for the object to be segmented. The user provides initial values and the algorithm segments objects accordingly. Semi-automatic segmentation overcomes some of the problems of manual segmentation but is still subjective and slower than automatic segmentation. Automatic segmentation is the third category that solves the problem of both manual and semi-automatic segmentation. The key advantages of this technique include:

- Saves a lot of time of experts.
- Provide the same results when used repeatedly.
- Performance is not affected with brightness and contrast of display screen.
- Result of segmentation is not affected by missing manual steps, data overload and fatigue.
- Require no user interaction and parameter tuning.

Automatic segmentation of three-dimensional medical images is a very difficult task. Most of the segmentation algorithms are semi-automatic and only a few automatic algorithms are available that can segment a structure without user interaction [9, 10, 11]. In medical imaging literature, different techniques have been used for medical image segmentation. These include but not limited to region growing [12], deformable models [13], skeleton based approach [14], neural network [15], level sets [16, 17], generalized cylindrical models [18], model based approaches [19, 20] and machine learning [21]. Wink *et al.* [14] presented a vessel segmentation algorithm that uses iterative tracking process for vessel extraction. The algorithm is very effective for high-resolution images but it fails when the resolution becomes very low. A neural network based approach is developed by Katz *et al.* [15] that is used for automatic segmentation of the aorta. Zhao *et al.* [17] combined level set and optimal surface technique for segmentation of the aorta from four-dimensional medical images. An adaptive region growing approach is developed by Pohle *et al*. [12]. The algorithm is used to segment aorta from medical images without user interaction. Flehmann *et al.* [20] proposed an automatic algorithm for segmentation of the aorta from three-dimensional images. The algorithm combines fast marching and model based approach for automatic detection and delineation of the aorta. Hussain *et al*. [26] developed an automatic segmentation pipeline that combines Hough transform and connected threshold techniques for automatic identification and segmentation of the aorta. The algorithm is very faster for three-dimensional images and can segment low as well as high-resolution of images without user interaction. All these algorithms are application specific and cannot be used for all types of segmentation. Automatic segmentation overcomes the problems of manual and semi-automatic segmentation and is the need of practical applications. A standard automatic segmentation algorithm is still pending due to various factors. Most of the algorithms require very high resolution of images and fail to segment low contrast of input images. Many of these algorithms are application specific and segment just a well-defined part of human body. Some of these algorithms require parameter tuning and take a very long processing time.

II. CHALLENGES WITH AUTOMATIC SEGMENTATION

There are various reasons due to which automatic segmentation is a very challenging and unsolved problem. The problems to automatic segmentation (Fig 1) may occur due to the imaging system and modalities used for image acquisition such as X-rays, Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), ultrasound etc. Sometime segmentation becomes challenging due the problems related to the patient to be diagnosed and treated. These problems include variation of patient anatomy, disease, and movement during image acquisition. Problems encountered due to medical applications such as real time computation and lack of sophisticated tools etc. also make automatic segmentation difficult. Similarly, complications may also arise during actual processing of medical images that are noisy, homogeneous and difficult to process. In this section, we have categorized these challenges into four categories (Fig 1) and experimentally tested their effects on the commonly available automatic algorithms.

A. *Imaging System-related Challenges*

In medical imaging, the various modalities used for

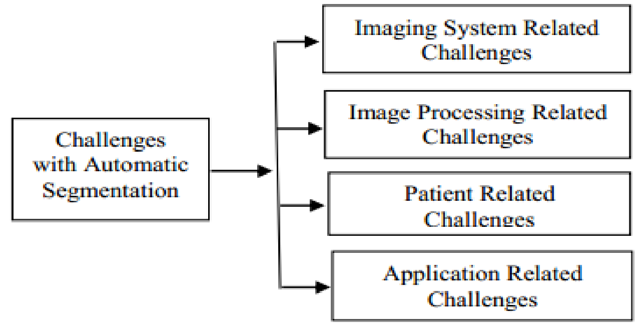

Fig. 1 Classification of Challenges with Automatic Segmentation Algorithms

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acquisition of images have their own strengths and limitations. In automatic segmentation, various challenges arise due to the difference in characteristics of these modalities. The problems that are related to imaging modalities and general segmentation results are summarized in the following section.

1. MR Imaging Artifacts: There are various challenges that arise during the acquisition of MR images and affect the performance of automatic segmentation. These include:

- Partial Volume Effect: There is no consistency in the pixels intensity values, and boundaries of an image blurs due to presence of a mixture of intensity classes (Fig 2 (a)).

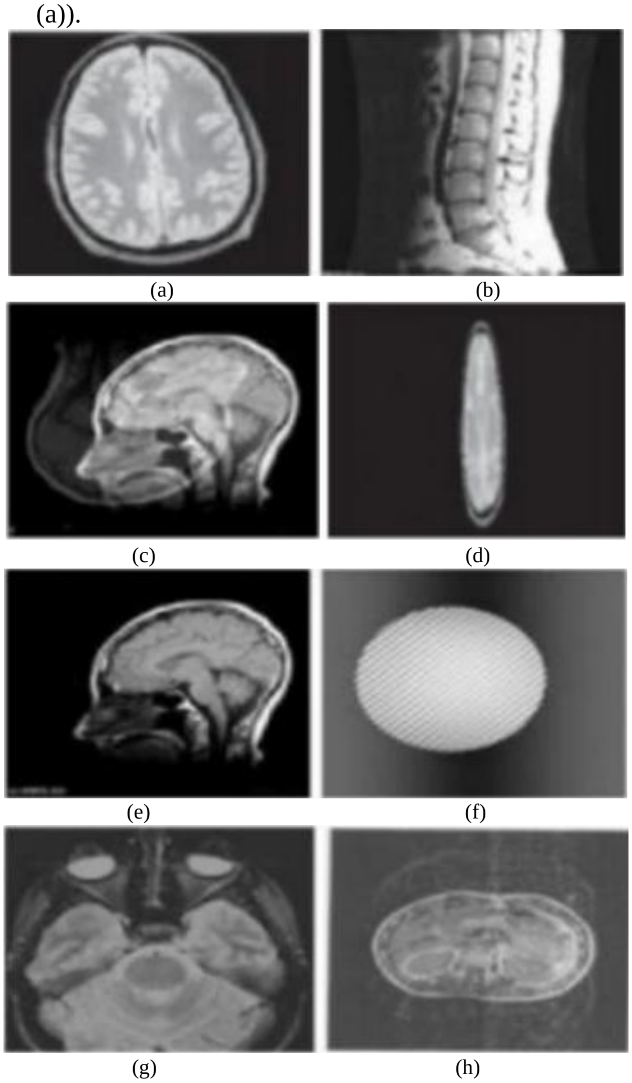

Fig. 2 MR imaging artifacts that make segmentation challenging: (a) Partial volume affect that causes image blurring at the boundaries. (b) RF noise artifact that occurs due to failure of RF shielding. (c) Homogeneity of image that makes the process of segmentation very difficult. (d) Gradient artifact that arises due to problems in gradient system during image acquisition. (e) Wrap around artifact that occurs when the FOV is smaller. (f) The artifact of Gibbs ringing that creates lines in the image. (g) Susceptibility that occurs when an object is present in FOV. (h) Motion: Movement of Objects during acquisition

- Radio Frequency (RF) Noise: RF shielding that prevents external noise to enter into the image detector fails and the image becomes noisy (Fig 2 (b)).
- Image Homogeneity: Missing boundaries and low difference in intensity values make the image difficult to segment (Fig 2 (c)).
- Gradient Artifact: Problem occurs due to failure of gradient system during image acquisition (Fig 2 (d)).
- Wrap around Effect: Problems occur when the organ to be imaged is larger than the Field of View (FOV) (Fig 2 (e)).
- Gibbs Ringing. The effect that arise due to presence of lines on the image (Fig 2 (f)).
- Susceptibility: Problem occurs when an object of lower or higher magnetic susceptibility is present in the FOV (Fig 2 (g)).
- Motion. Movement of object during image acquisition (Fig 2 (h)).

2. CT Artifacts: The challenges with CT images include streak, motion, beam hardening and bloom artifacts.

- Streak: Artifact arises due to materials such as metals or bones that block most of the X-rays (Fig 3 (a)).
- Motion: Movement of object of interest during image acquisition (Fig 3 (b)).
- Beam hardening: The problem occurs due to attenuation (Fig 3 (c)).
- Ring Artifact: The artifact arises due to failure of detectors elements of CT scanner (Fig 3 (d-e)).
- Bloom Effect: Change that occurs in the structure of the object and make automatic segmentation difficult (Fig 3 (f)).

Other challenges that arise due to imaging systems such as difference of image modalities, image dimension, quality of the image and noise present in the image also make the automatic segmentation very difficult.

3. Image Modality: For acquisition of medical images, different image modalities are used such as X-rays, CT, MRI and Ultrasound. Each modality has its own characteristics and used for different application. Some modalities are used for image acquisition of soft tissues while other are used for hard tissues and bones. The difference in intrinsic properties of each imaging system makes the automatic segmentation challenging (Fig 4).
4. Image Dimension: With modern imaging technology and rapid advancement, increase occurs in size and dimension of images that require advanced techniques for segmentation. In medical imaging environment, the images with three and four dimensions are commonly used for analysis of body structures. High dimensional images require advanced techniques and the algorithms for low dimensions may not segment three and four-dimensional images.
5. Image Quality: Quality of input image such as homogeneity, low contrast, noise present in the image and other specific features directly affects the performance of automatic segmentation algorithms and

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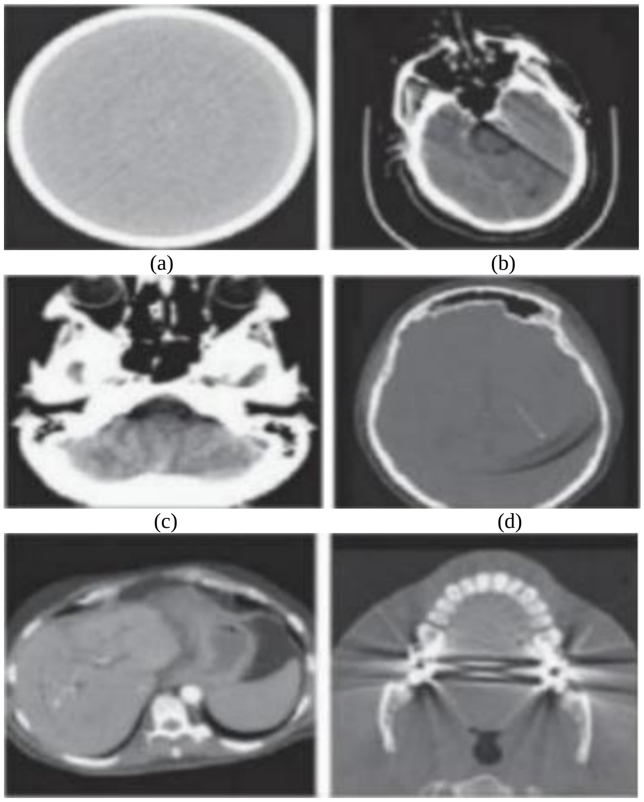
make the process of segmentation very challenging (Fig 9-12).

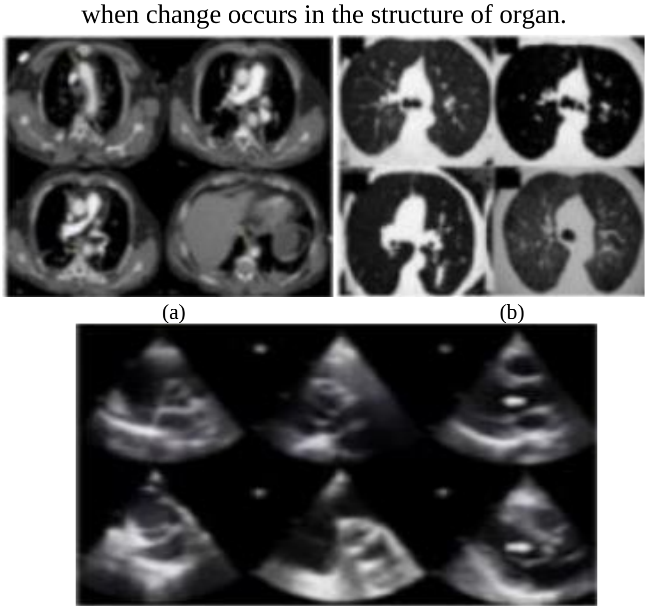
B. Image Processing-related Challenges

For the purpose of analysis, ROI recognition, segmentation, noise removal and other different applications, various operations are performed on medical images.



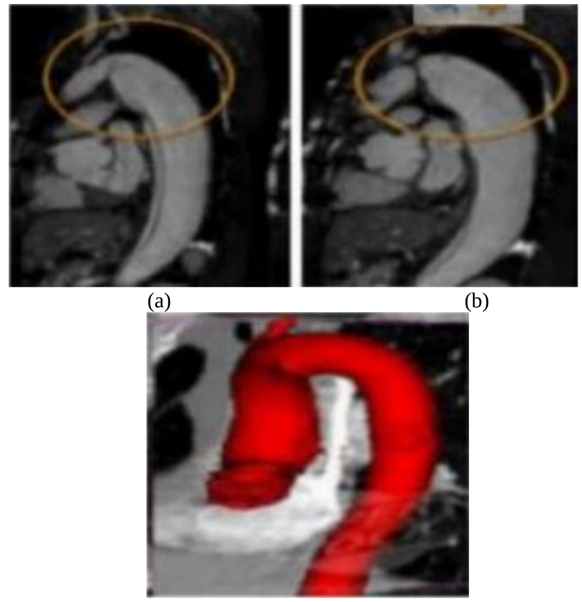
(a) (b) (c) (d) (e) (f)

Fig. 3 CT artifacts that affect segmentation process: (a) Streak artifact that arises due to obstruction of X-rays (b) Motion: artifact due to movement of organ to be imaged (c) Beam-hardening: problem that arises from attenuation (d-e) Ring artifact: problem in CT scanner (f) Bloom artifact: when change occurs in the structure of organ.



(a) (b) (c)

Fig. 4 Image modalities that affects segmentation: (a) CT image (b) MR image (c) Ultrasound image



(a) (b) (c)

Fig. 5 Effects of image features on performance of segmentation algorithms: (a-b) Object dis-connectivity represented by circles in the images (c) Object shape and angle variation.

Challenges may arise during the process of representing ROI in computer system, identifying image features, process of controlling segmentation and automation. These factors are discussed in the following section.

1. Image Type: An input to the segmentation algorithm may be binary, gray scale or color image. Each image has its own features and a single algorithm cannot be applied for all types of images.
2. Image Features: Various features of the input image such as contrast, size, resolution, color, gray level, image holes, curves, dis-connectivity of ROI, shape and angle increase the user interaction, affect the result quality and make accurate segmentation very difficult as shown in the Fig 5.
3. Process of Automation: Automatic segmentation is very important in medical applications that automatically delineate the region of interest from the image. It reduces user interaction and saves time and effort. The automation criteria depend upon the ROI attributes such as size, color, shape and structure. The problem is how to set criteria for automatic identification. A single criterion may not be used for all types of structures. For example, a circle can be used for automatic extraction of circular objects but cannot be applied for objects with arbitrary shape.
4. Manual Initialization: To limit the search space and separate a particular region of an image, manual initialization of parameters is required. It is very useful for an interactive system to control the process of accurate segmentation but creates a problem for fully

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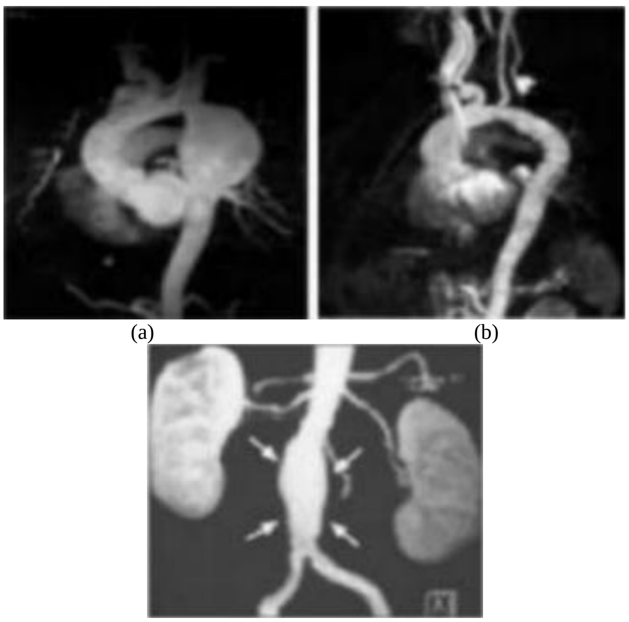
automatic segmentation techniques. Selection of optimal values and parameter setting for each image is very time consuming and trial and error based task. A single algorithm will produce different results of the same image with changing parameters as shown in Fig 7 in the experiments section.

5. Uncertainty in the Boundaries of ROI: The purpose of medical image segmentation is to separate a specific structure for easier analysis and treatment planning. Automatic boundary detection algorithms are used to accurately segment a particular region but an image with missing boundaries, disconnectivity, noise, homogeneity, and lack of texture make the segmentation very difficult and the algorithm fails to segment the ROI in such cases.



(a) (b)

(c)

Fig. 6. Variation in the shape of ROI due to disease: (a-c) Abnormalities in the aorta make automatic delineation difficult.

C. *Patient-related Challenges*

In the process of medical image segmentation, some of the problems arise due to the patient to be diagnosed and treated. These problems are specific to the patient such as anatomy of the one patient that is different from other patients, abnormality that may cause variation in the shape and structure or an object of interest or object movement during the process of image acquisition. Similarly, data collection about a patient is difficult that affect the development of a reliable system for treatment planning and analysis. Some of the most common challenges that occur during the process of automatic segmentation are summarized in the following section.

1. Anatomy Variation: Variation in human anatomy exists between two different individuals that may be due to age of the patient, height, disease, or other natural factors that increase user interaction and require different criteria for segmentation. For identification of each structure, a different set of parameters are required and one single criterion cannot be applied for images of different individuals. The anatomy variation that occurs in aorta of three different individuals is shown in Fig 8.
2. Disease Type: In medical environments, most of the segmentation algorithms are application specific and are used to segment just a well-defined region of the image. Variations in structure and shape of the objects may occur due to some abnormalities (Fig 6 (a-c)). During the process of segmentation, the same criteria cannot work for all objects and thus reduce the automation.
3. Motion: In practical imaging environment, the organs to be imaged such as heart, lungs etc. are usually not stationary during the acquisition period. Due to the motion of objects, some artifacts arise which make segmentation challenging. Examples of these artifacts include image blurring and ghost effects.
4. Data Collection Issues: The issues that arise during data collection such as data privacy, collaboration with hospitals, communication gap, search for research oriented clinicians, and data availability to the computer scientists are the different factors that affect general as well as automatic segmentation of images.

D. *Application-related Challenges*

Lack of ground truth, real time computation, anatomy representation in a computer system, lack of generalized algorithms, tools etc. are related to the medical application and makes the automatic segmentation very challenging.

1. Lack of Ground Truth: Most of the automatic segmentation algorithms are organ specific and have their own criteria for accurate segmentation of the desired structures. The problem is how to know that the performance of one algorithms is better than the other algorithm. In medical applications, the segmentation results of automatic algorithms are compared with manually segmented results that are highly variable. Complications arise for automatic segmentation of images from the unavailability of ground truth to compare the results.
2. Real Time Computation: For medical applications, real time computation is desirable to provide reliable and effective results for diagnosis and treatment. The results of a segmentation technique must be accurate, reliable and repeatable that must not lead to false decisions.
3. Lack of Generalized Algorithms: There is no universal algorithm for all images and most of the algorithms are specific to imaging modalities, body part to be studied and type of application.
4. Need of Basic Knowledge: It is very difficult to represent the human anatomy in a computer system. The problem is how to define an object of interest, as the object itself is further divided into other objects and may vary significantly.
5. Lack of Sophisticated Tools: Due to unavailability of reliable software tools for automatic segmentation, doctors still prefer manual and semi-automatic segmentation. A number of software applications are

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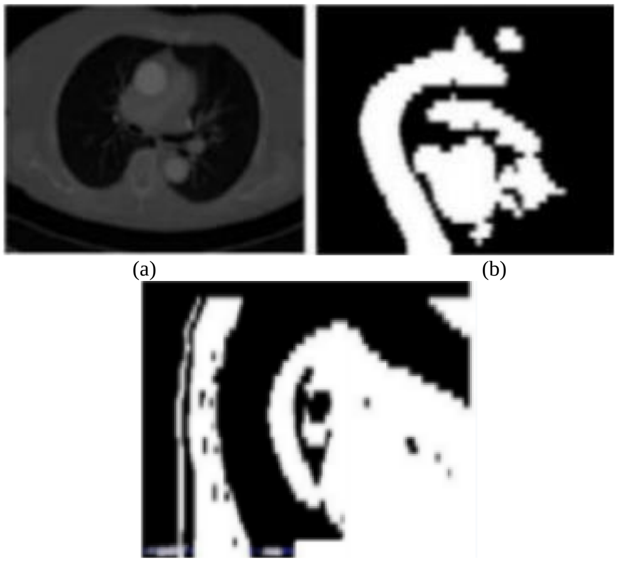
available, [22, 23] but are application specific and cannot used for different structures or for the same structure with different attributes.



(c)

Fig. 7 Manual initialization as a challenge for fully automatic image segmentation algorithm: (a) One slice of original MR image (b-c) Change in parameters produces different results of the same image

6. Absence of Vivo Benchmarks: Due to ill-defined segmentation problem and unavailability of standard technique for comparing the algorithm performance, it is difficult to say that one technique is better than the other is.

(c)

Fig. 8 Anatomy variation that affects the process of automation: (a-b-c) Variation in the shape of aorta among different people.

7. Selection of Suitable Algorithm: Selection of a suitable algorithm for meaningful segmentation depends upon the image type, image features, parameters to be extracted and purpose of segmentation. Algorithm developed for one application may not work for other applications.
8. Qualitative Analysis instead of Quantitative Analysis: Based on the difference of segmentation results and unavailability of gold standard, quantitative comparison is very difficult. Automatic segmentation is compared with manually obtained segmentation but this approach does not guarantee the accurate results due to variability in manual segmentation.

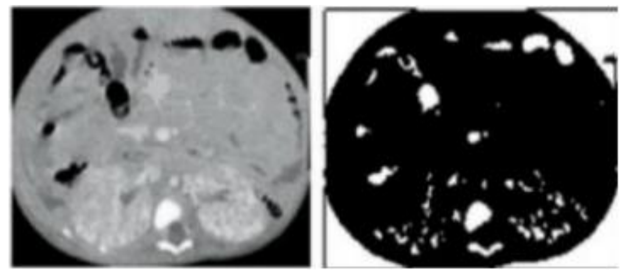

(a) (b)

Fig. 9 Image noise that affect the result of segmentation algorithm: (a) Original 2D MR image with noise (b) Segmented image (Lower threshold 20 and upper threshold 200).

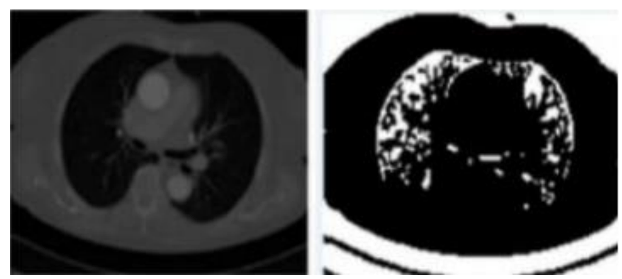

(a) (b)

Fig. 10 Image quality that affect the result of segmentation algorithm: (a) Original 2D MR image (b) Segmented image (Lower threshold 20 and upper threshold 200).

III. EXPERIMENTS

Experiments show that the segmentation algorithms are affected by challenges that arise due to input image, imaging system, patient to be treated, or application developed for segmentation. Fig 7 shows result variation due to changing seed points, threshold values and many other pre-processing parameters. The algorithms give different results by providing different segmentation parameters. A slight change in values may cause a large difference of the results. With the same set of parameters, one algorithm produce different results of the same image. When anatomy variation occurs (Fig 8), the algorithms fail to segment an object of interest. The algorithm developed for the segmentation of one structure may not be applied to other structure. Similarly, image noise, quality, process of automation, contrast and

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image homogeneity (Fig 9-12) makes the segmentation of the image very difficult.

IV. SUMMARY ANALYSIS

Both the analysis and experiments on real medical images demonstrate that no single method can best handle all the anatomic structures from an image in medical image segmentation. The fundamental aspects of medical images such as quality of the image, modality of image acquisition, user interaction, image homogeneity and other features should be considered for the development of a fully automatic segmentation approach that can be used in practical applications. Table I shows the experimental data values quantifying the varying effects of challenges discussed and its effect on commonly used segmentation algorithms. These algorithms include adaptive region growing [12], deformable model based approaches [19, 20, 24] and machine learning techniques [25]. From table (Table I) it is clear that image quality, homogeneity and features of images affect most of the segmentation techniques. Similarly, manual initialization, human anatomy variation and dimension of the image data also make the automatic segmentation difficult and challenging.

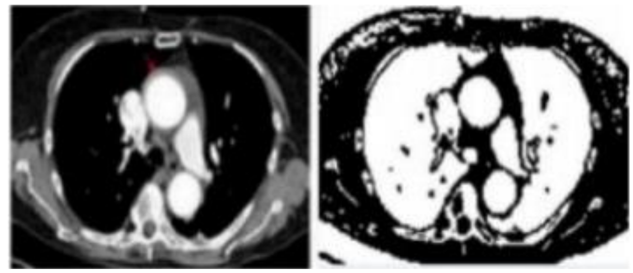
V. CONCLUSION AND FUTURE DIRECTIONS

Image segmentation plays very important role in treatment planning and analysis. Up to now, there is no reliable algorithm to segment the ROI from all types of 3D image data. A standard algorithm for practical applications is awaiting due to various factors. In this study, the growing interest of automatic image segmentation is discussed and various segmentation algorithms are implemented to identify and explore the factors due to which automatic segmentation is still a challenging and pending problem. The major problems for state of the art approaches include:

- Most of the segmentation algorithms are semi-automatic that require user interaction and are difficult for use in practical applications.
- Some of the algorithms that are automatic require very high resolution of images for segmentation.
- Usually the algorithms are application specific and the algorithms developed for one application may not work for other type of application.
- The performance of medical image segmentation algorithms is influenced by various factors, and there is always a trade-off between factors.

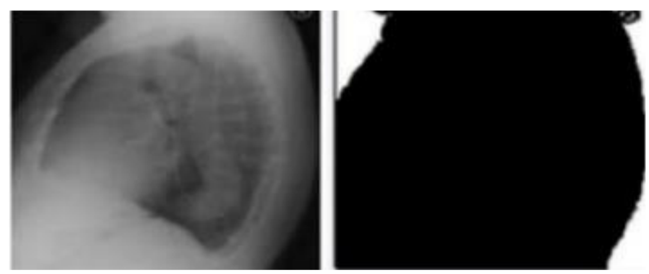
All these are the important problems, and need to be addressed in future methods in order to make segmentation a truly viable and robust technology for practical applications. In working towards solving some of these problems, one possible solution is to develop image-preprocessing techniques to enhance the quality of the image before actual implementation of segmentation algorithms and reduce computation time. The acquisition of high-resolution images increases patient exposure time inside the machine and require costly resources. Similarly, clear images of some objects are very difficult or impossible to capture.

Another direction is to exploit the developments in the current technology in order to develop fully automatic methods for faster segmentation with least processing cost and user interaction. Moreover, a prior knowledge about human anatomy can be incorporated to develop a segmentation algorithm that can be used for practical applications.



(a) (b)

Fig. 11 Image contrast as a challenge for segmentation. High contrast images are easier to segment: (a) Original high contrast image (b) Segmented image (Lower threshold 20 and upper threshold 200).



(a) (b)

Fig. 12 Image homogeneity affects segmentation results. Homogeneous regions are difficult to segment: (a) Original homogeneous image (b) Segmented image (Lower threshold 20 and upper threshold 200)

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TABLE I. THE EFFECTS OF SEGMENTATION CHALLENGES ON COMMONLY USED ALGORITHMS FOR SEGMENTATION OF REAL MEDICAL IMAGES

Segmentation Algorithms	Image Quantity	Intensity Homogeneity	Imaging Modality	Organ Features	Anatomy Variation	Manual Initialization	Image Contrast
Pohle et al. [12]	Yes	Yes	Yes	Yes	Yes	No	Yes
Wink et al. [14]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Katz et al. [15]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deschamps [16]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zhao et al. [17]	Yes	Yes	No	Yes	Yes	Yes	Yes
Kovacs [19]	Yes	Yes	No	Yes	Yes	No	Yes
Rahman et al. [20]	Yes	Yes	No	Yes	No	No	No
Rueckert et al. [24]	Yes	Yes	No	Yes	Yes	No	Yes
Zheng et al. [25]	Yes	Yes	No	Yes	No	No	Yes

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