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Comparison of image processing techniques for segmentations of images in healthcare in speed of executions

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Abstract

Advancements in computing technologies have resulted in high performing low cost computers which have been exploited in healthcare. IPTs (Image Processing Techniques) have been important and widely used for medical image analysis. Images obtained from medical imaging modalities have been analyzed for obtaining quantitative information or data where segmentations play an important part. Image segmentations in computer vision are applied to various fields including medical imaging, video surveillances, object detections/ recognitions, IRs (Image Retrievals) and automatic traffic control systems. Medical image segmentation approaches are utilised for diagnosis and treatment planning as they extract useful information fro pictures and with the basic goal of improving digital picture analyses. However, assessing performances of segmentation algorithms has become a must in order for obtaining appropriate results. This study highlights different techniques used in segmentations of medical images with a comparison of their performances in segmentations. The base objective of this study is to examine segmentation algorithms in a detailed way and thus promote further and deeper researches in combinations of approaches for effective and accurate segmentation of human body parts from medical images.

Keywords: IPTs (Image Processing Techniques), IRs (Image Retrievals), medical images.

1. INTRODUCTION

One significant goal of IMPTs is acquiring crucial information from [1] images. IMPTs work using pixels which are two-dimensional squares [2]. Segmentations are component of IMPTs and divide digital pictures into smaller portions called segments (groups of pixels) for analyzing significant information. These procedures assist in converting digital images into meaningful data which can be easily examined. For example IMPTs use segmentations for object detections including faces, fingers, and irises, traffic controls systems, and computer vision. Segmentations also minimize image IRs by dividing pictures into ROIs (regions of interest). Examinations of medical pictures based on ROIs include malignant cell detections, differentiation of tumours/tissues/lesions. Segmentation findings are extremely significant and require high levels of accuracy in terms of medical diagnosis when clinicians base their judgments based on these outcomes. Segmentations also help in studying anatomical structures, locating abnormalities and measuring tissue/tumour volumes, thus helping treatment therapies or planning. The characteristic extracted by segmentations are based on differentiations of colours or intensities or textures [3] or image recognitions. Segmentation approaches rely on specific conditions for classifying photos that pique user's interest [4]. Many studies have suggested segmentation algorithms over the years and they divide their processes into two namely discontinuity and similarity based segmentations. Discontinuity segmentations basically separate pictures based on intensities and divide images into similarity based regions [5].Figure 1 shows comprehensive categorizations of segmentation approaches.

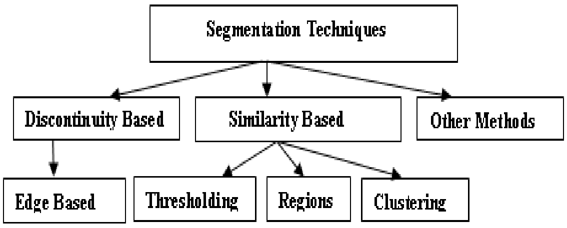

Fig. 1 – *Image Segmentation Approaches*

Picture segmentations of medical photographs have a few issues like they are frequently subjected to a variety of distortions that might degrade image quality. This implies correct image segmentation approaches need to tailor their procedures for retaining relevant information and obtaining comparable quality regions [6]. Many studies have projected the complexity of segmenting pictures. This research compares existing picture segmentation techniques, as well as their advantages and disadvantages. The segmentation process can be carried out using a variety of techniques. The comparison of image segmentation algorithms is used on medical pictures in this study. Following this introductory section, a detailed review of literature of feature extraction techniques is section two. Section three discusses issues and challenges while section four concludes this paper.

II. LITERATURE REVIEW

Medical modalities capture human body parts and convert them into images where MRIs (Magnetic Resource Imaging) are the most extensively used [7] MRI are controlled corresponding to their longitudinal relaxation time frames (T1) and transverse relaxation time frames (T2). The signal intensities on T1/T2 images relate to hum tissue characteristics. MRIs are dynamic and flexible which allow vary image contrasts by using different pulse sequences and changing their imaging parameters. MRIs of the human body obtain structural information about brain or liver or chest or abdomen or pelvis which aid in diagnosis and subsequent therapies. Figure 2 illustrates some of the artifacts found in medical pictures.

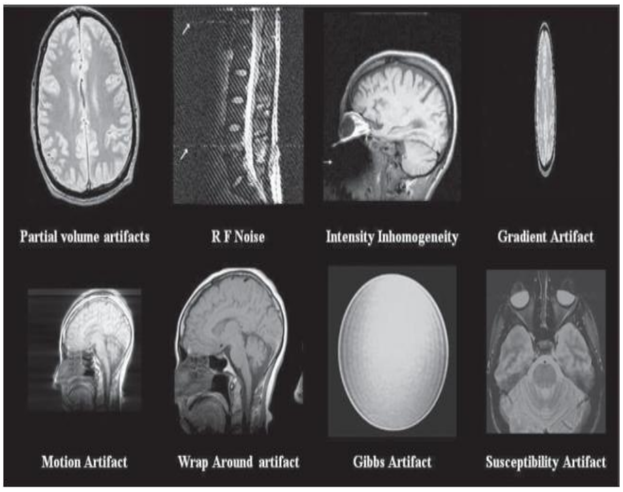

Fig. 2 – *Medical Image Impurities*

The categorization of segmentation techniques has been done in a variety of ways [8] but based on picture's grey levels or textural properties [9.] where gray level divisions can be based on amplitudes [10] or edges [11] or regions [12] as detailed below:

• Amplitudes of Histogram features: These segmentations work on picture's histograms where thresholding values are used. These grey level thresholding approaches are useful in segmenting pictures with bright patches or objects set against variable background grey levels and separate patches/objects from backdrops based on threshold values where homogenous zones are created. By using appropriate threshold values, pictures are transformed into binary images, minimising the complexities for further processes [12]. The mathematical formulations of thresholding procedures are depicted as Equation (1)

$$T = \{ x, y, L(x,y), f(x,y) \} \quad \ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

Where (x,y) represents pixel positions in pictures, L(x,y) represents local property of pictures, and f(x,y) represents pixel intensity values. On the basis of grey pixel's values, and their neighbourhood properties, thresholding processes can be Global (based only on picture's grey levels), Local (picture's grey levels and local attributes) and dynamic or adaptive (picture's grey levels, neighbourhood properties, and pixel coordinates)

o Global Thresholding: The grey levels (histograms) determine threshold values and based on biomodal and multimodal histograms, threshold values may be singular or multiple.

o Simple/Single Thresholding: This procedure is a straightforward approach and used for bimodal pictures. Threshold values are determined at random using means of peaks or the valley points. Pixel intensities of pictures are compared to threshold values and pixels exceeding these values are evaluated, and it eventually put into sub-regions, thus generating reasonable ROIs. In input pictures f(x,y), the threshold outputs of the pictures g(x,y) are computed using Equation (2)

$$g(x,y) = \begin{cases} 1, & \nabla f(x,y) \geq T \\ 0, & otherwise \end{cases} \quad (2)$$

o Multiple Thresholding: It works similar to singular thresholds, except that n distinct threshold values are used. Multiple thresholding values are required when input pictures have multiple objects.

o Optimal Thresholding: When overlapping objects are found in histograms, the best thresholding strategy is differentiating class variances (image data attributes) for threshold values. Otsu approaches are unsupervised approached that employ optimum thresholding and iterate over all conceivable threshold values for computing spread for pixel levels on each side of thresholds including pixels that lie in foregrounds or backgrounds. The main aim of this approach is to discover values at which foregrounds and backgrounds have minimal spreads.

o Local Thresholding: On non-uniform backdrop illuminations, global thresholding approaches fail and to overcome this failure, methods based on mean and standard derivation ( ) of surrounding pixels is used where means standard deviations are used to obtain threshold values. Several approaches have been presented for histogram based optimum picture segmentations [13.] Figure 3 depicts a medical image, its histogram and segmented image using thresholding where 3 peaks (maxima) aer separated by two minima in the histogram which is the selected threshold for segmentations.

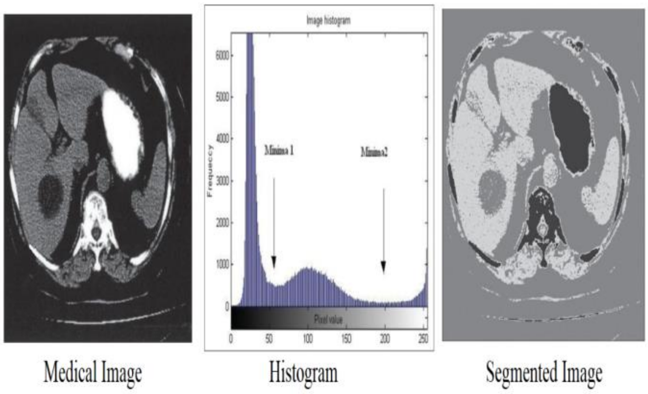

Fig. 3 – *Segmentation results by thresholding*

• Edge based segmentations: These are very popular approaches for picture segmentations where identification of edges are based on marking discontinuities found in grey levels, colours, and other factors while indicating object boundaries. These approaches separate pictures into sections based on picture borders. Prewitt, Sobel, Roberts (1st derivative type) and Laplacian (2nd derivative type), Canny, and Marr-Hilclrath edge detectors are all examples of edge detection operators which are based on gradient (derivative) functions. Furthermore, edge based segmentation approaches build borders by integrating detected edges into edge chains where false/weak edges are eliminated using thresholding operations. Edge relaxations,[14], Border detections [15], and Hough transforms based segmentations are different edge based segmentation approaches. The stages in the generalised method for edge-based segmentation are as follows. (i) detecting picture edges using derivative operators (ii) measuring edge strengths using gradient amplitudes (iii) keeping all edges with magnitudes greater than threshold T (removing weak edges) (iv) determining locations of cracked edges where crack edges are either accepted nor denied based on trust levels received from predecessor and successor edges

(v) Steps 3 and 4 are repeated with different threshold values to determine closed borders and image segmentations are thus completed. Figure 5 depicts the outcome of edge-based analysis. segmentations using different filters and edge detection techniques on medical images.

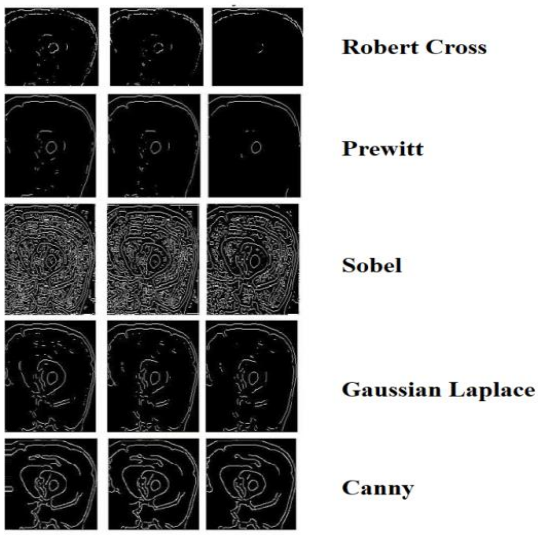

Fig. 5 - *edge based segmentation of medical image*

• Region based segmentation: The notion of homogeneity underpins region-based methods: pixels with similar qualities are grouped together to produce homogeneous regions. The most common criterion for homogeneities are grey levels of pixels[17] and described in equation (3)

$R1 \cup . R2 \cup . R3 \cup .... \cup . Ri = I$ …………….(3)

where R1, R2, R3, …Ri are the region in the image I, and further, $R1 \cap R2 \cap R3 \cap ... \cap Ri = 0$. According to the set theory of homogeneity and region growths, region based segmentations cane further separated into region merges, region splits and splits and merges. Seeding points are necessary to start region merges and segmentation outcomes are reliant on the selected seeds. Regions are grown iteratively by merging neighboring pixels and based on merging criteria and the process is repeated until all pixels have been allocated to their proper areas. Region splits work in a manner similar merges, but constantly split pictures until no more splits are feasible. Splits and merges approaches combine splits and merges while using quad quadrant trees to represent data where pictures are divided into four quadrants when attributes are non-uniform. Subsequently, four adjacent squares are combined based on the region's homogeneity of segments. The splits and merges are iterated until no more executions are possible. These approaches have the following steps: defining homogeneity criteria; dividing pictures into four square quadrants; when resultant squares are not homogenous, they are divided it into four further quadrants; combining two or more surrounding areas that match homogeneity criteria; continuing splits and merges until no more regions of pictures can be divided or merged. In addition to these approaches, watershed segmentations based on topographies and hydrographies are other region based segmentation approaches [18]. The outcome of region based segmentations are depicted as Figure 6.

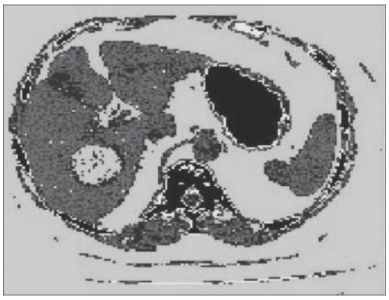

Fig. 6 – *Segmented image using region based technique*

• Segmentations based on textural features: Picture's segmentations or classifications based on their textural characteristics are very important and have been used or proposed by prior studies. The main aim of textural segmentations are splitting pictures into areas with different texture features, whereas classifications categorize these divided regions. Textures can be described as a collection of interconnected parts [19] based on tones and structures which may be fine, coarse, smooth, or grainy. Structures are spatial links between pixels, whereas tones are pixel intensities [20] Textures can also be described as spatial configurations of textural elements (textones) which have periodicity between them. Textural primitives are groups of pixels that represent the simplest or most fundamental sub-patterns and can be extracted statistically or syntactically or structurally or spectrally. Textures can be extracted as a set of statistical characteristics and expressed as vectors in multidimensional feature spaces. The statistical characteristics might be based on the grey level of an image's first-order, second-order, or higher-order statistics. A probabilistic or deterministic decision method assigns the feature vector derived by patterns to their specified class [21]. In syntactic approaches, textures are defined by texture primitives which get spatially ordered according based on rules to form full patterns. The study in [22] compared structural patterns and syntax of language in syntactic feature based pattern recognitions. Textures are defined by spatial frequencies and assessed using autocorrelations of textures in spectral approaches. Co-occurrence matrices based on statistical description of picture's grey levels,[23] grey level run lengths,[24] fractal textural descriptions,[25] syntactic,[26] and Fourier filters are all some of the approaches used in textural feature extractions and classification [27]. In the comparisons of the afire said approaches, it was found that spectrum frequency based methods were less efficient, but statistical methods were particularly beneficial for random patterns/textures, and syntactic or structural methods yield superior results for complicated patterns..

• Others/Model based segmentations: The underlying idea in these approaches is that organ structures have repeating geometries that could be used for modelling based on probabilistic shapes and geometrical changes. These approaches include: registration of training data, probabilistic representations of variations in registered data, and statistical influences between models and pictures which can be utilised as constraints in segmentations. AIs (Artificial intelligences) based approaches have been widely used to create automatic segmentations of pictures where they have categorized as supervised and unsupervised approaches where the latter often require operator participations after segmentations are completed whereas former methods demand operator engagement throughout segmentation processes. To assure repeatable outcomes, unsupervised approaches are preferred [28], however operator inputs are still mandatory for error corrections when results are unsatisfactory.

• Supervised methods: In the supervised category, we can place mostly Artificial Neural Network (ANN) based algorithms. ANN is composed of large number of interconnected processing elements (artificial neurons) working in unison to solve specific problems. The main advantages of ANN are ability to learn adaptively, using training data to solve complex problems. capability of self-organization; it can create its own organization depending upon the information it receives during learning time capability of performance in real time because of parallel configuration. In case of ANN, learning is achieved by the adaptation of weights and bias of the neurons with respect to the training procedure and training data. ANN has been widely used for segmentation and classification purposes in both supervised and unsupervised modes [30]

• Unsupervised methods: Most unsupervised algorithms are cluster based and do not require training. K-mean, also known as Hard C-mean, and Fuzzy C-means are popular clustering techniques where K-means approaches generate hard segmentation results, but fuzzy C-mean approaches produces soft segmentations that can be transformed to hard segmentations by enabling pixels to belong to clusters with the highest membership coefficients. The main aim of clustering is to create decision boundaries from unlabeled training data [31]. In multidimensional feature spaces, clustering amount to discovering natural groups which is an issue as these feature spaces might contain clusters of various forms and sizes. A variety of functional cluster definitions have been proposed including cluster patterns that are more similar to one another than patterns from separate clusters. Image segmentations are also grouping [32] of pixels are grouped into attribute regions based on texture's feature vector computed in pixel's immediate vicinity. Fuzzy clustering is a useful approach for categorising a set of data points into numerous groups with different characteristics.

III. DISCUSSIONS

Medical picture segmentations have three main issues namely noises that change pixel intensities, variations in intensities/homogeneities particularly with finer elements like tissue parts which gradually change over the length of images, and images with partial volume averaging where individual pixel volumes contain a mixture of tissue classes. These factors prevent intensities being considered in segmentations. Many segmentation approaches have been suggested in the last decade to improve the accuracy and efficacy of segmentations. However, no single approach can be called successful. As a result, research in this area is an ongoing process with the aim of enhancing effectiveness of image segmentations. Comparisons between Segmentation approaches are listed as Table 1.

Table 1 - *Segmentation Approaches in comparison*

Segmentation techniques	**Description**	**Advantages**
Thresholding Methods	based on the histogram peaks of the image to find particular threshold values	no need of previous information, simplest method
Edge Based Method	based on discontinuity detection	good for images having better contrast between objects
Region Based Method	based on partitioning image into homogeneous regions	more immune to noise, useful when it is easy to define similarity criteria
Clustering Method	based on division into homogeneous clusters	fuzzy uses partial membership therefore more useful for real problems
ANN Based Method	based on the simulation of learning process for decision making	no need to write complex programs

Despite the fact that many approaches have been suggested in medical picture segmentations, it remains a complicated and difficult subject, since problems start shooting up as soon as the images are captured and require pre-processing or filtering. For IMTs, artifacts in medical pictures like noises, non-sharp edges, regions that require restorations, partial volumes and variable intensities/homogeneities increase complexity of processing. Threshold approaches are low cost computing methods and are ideally suited for real-time applications. However, these approaches ignore spatial information and are extremely susceptible to noises resulting in fake/ missing edges. Pictures influenced by sunlight, noises, poor contrasts result in not so accurate global thresholding making it challenging to choose the right threshold values. The drawbacks of edge based methods can be due to noises which impact their performances resulting in false/weak edges and hence reducing segmentation results accuracies. For comprehensive segmentations, edge detection approaches must be used in combination with region based approaches. The disadvantage of region-based segmentation is that there is a risk of under- and over-segmentation of picture areas. This challenge, however, may be solved in two ways: ideally determining the segmentation criterion (for which numerous algorithms based on artificial intelligence approaches have been created), and By merging the region-based and edge-based approaches [33]. Active shape and appearance models, deformable models, and level-set based models are all examples of model-based segmentation approaches. Their drawbacks include: They need human engagement to set up an initial model and choose acceptable parameters. Standard deformable models can also show signs of deformation and poor convergence to concave boundaries. When compared to segmentation of medical images using simple grey level based approaches, texture based methods are well suited for segmentation of medical images. [34]. Although a variety of neural network-based algorithms for texture-based segmentation and classification have been developed with high classification accuracy, most of these texture classifier algorithms require extensive supervision and training; their performance is sensitive to training parameters and is negatively affected in the presence of noise. Guided picture segmentation and classification methods can be expensive, complex, or even impossible to pick and label accurately training data with its true category. ANNs require classifiers to be trained before they can be applied to segmentation and classification problems. Furthermore, the entire work of picking training data set and training must be performed for other data sets, analysis of different pictures of different types and formats. Clustering techniques include the following drawbacks: (a) sensitivity to the initial partition matrix (b) halting criterion (c) solution may become trapped at local minima. As a result, clustering approaches may not produce the optimum answer, and there is no one perfect clustering algorithm for every application. To determine the optimal algorithm, a variety of alternative algorithms must be explored. Quantitative data was analyzed for a more targeted approach, ensuring that the data or information gained is useful. Furthermore, the data can be represented numerically and statistically. Overall, there are 3 subjects were provided for extracting important ROIs from the images and execution times noted. Figure 6 depicts the execution times of segmentation techniques for a single Image while Figure 7 depicts three different subjects and their comparative segmentation time in seconds.

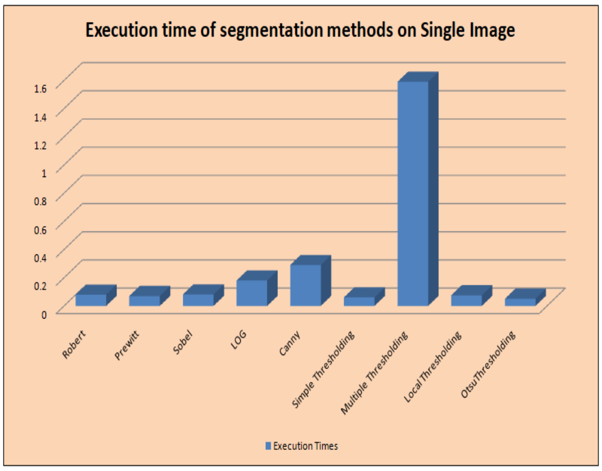

Fig. 6 – *Execution time in seconds Vs Segmentation Methods (Single Image)*

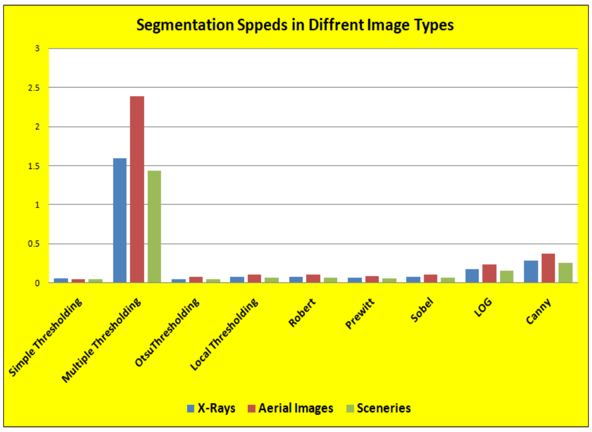

Fig. 7 – *Execution time in seconds Vs Segmentation Methods (Multiple Subjects)*

It can be seen from the above figures that Simple, otsu, local are fast in thresholding equivalent to Robert, Prewitt and sobel while multiple thresholding and canny detections based segmentations consume more time to segment. The times were noted for equal levels of accuracies namely 95%.

IV. CONCLUSION

This study is concluded with a comparison of several types of segmentation approaches, which were evaluated on medical, aerial, and natural landscape photographs. In this study, the efficacy of a few picture segmentation approaches was analyzed and compared. The universal segmentation method has become the key emphasis in medical image processing; therefore image segmentation has a bright future, especially in the medical industry. Despite several breakthroughs and fresh discoveries, a universally acknowledged picture segmentation approach that produces more accurate results has yet to be established, as image segmentation is influenced by a variety of elements, including the segmented image's aims. (medical, space, marine biology and etc.), picture continuity and spatial properties, as well as the nature of the source image. Nonetheless, the methodologies described in this study are adequate for a wide range of medical picture applications. These methods can be used to recognise and detect objects. Image segmentation, on the other hand, remains a difficult topic, particularly in medical image processing, due to the requirement to produce more precise and clear pictures with less noise. As a result, further study is needed to establish a globally acknowledged approach for improving disease and sickness diagnosis in the medical industry. Image segmentations refer to the division of pictures into mutually exclusive, non-overlapping, and homogenous sections for future use. The most fundamental and vital phase in every medical picture is segmentation, which allows for the characterization, broadening, and viewing of interesting areas. Other future scopes might be directed to employ metaheuristics algorithms based on various optimizations to increase the accuracy of different segmentation methods by optimizing parameters used in them..

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