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Hybrid and Multilevel Segmentation Technique for Medical Images

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***Abstract* - In this paper, we present a novel, fast, hybrid and bi-level segmentation technique uniquely developed for segmentation of medical images. Medical images are generally characterized by multiple regions, and weak edges. When regions in medical images are viewed as made up of homogeneous group of intensities, it becomes more difficult to analyze because quite often different organs or anatomical structures may have similar gray level or intensity representation. The complexity of medical imagery is well catered for in this technique by starting-out with multiple thresholding, applying similarity segmentation method, and resolving boundary problem with template matching technique, and then a region of interest (ROI) segmentation that involves finding the edges of the object of interest (OOI) at final stage. This technique can also be adapted to segmentation of non-medical images. A job is run using MATLAB and simple Grid computing as suitable environment.**

Keywords-Hybrid segmentation, Multi level Segmentation, Medical images, Template matching

I. INTRODUCTION

Medical images here refers to images of any part of the human anatomy taken with the aid of medical imaging devices/machines like magnetic resonance, computed tomography, X-ray, magnetic resonance angiography, et cetera, and taken in accordance with stipulated procedure. One of the main characteristics of medical images that distinguished it from other type of images is its weak edges [1], meaning there is a continuous flow of image information from one region to the adjacent one. This characteristic makes it more difficult to segment medical images into distinct regions for proper examination and accurate analysis in addition to the fact that no single segmentation technique is perfect in all respect [2].

Many of the existing segmentation methods have been applied on medical images with varying degrees of success, such as the works of [3] that used morphological gradient, [4] applied region growing, level-set, and normal methods of segmentation individually and fully automatic segmentation technique was realized based on the use of adaptive region-growing method by [5]. Nonetheless, for accurate segmentation, researchers have been turning to hybrid techniques as in [1] wherein hybrid of region growing and level-set was proposed, [6] used Modified fast marching and level set, [7] fused local geodesic active contours and a more global region-based active contour, while [8] combined region growing and edge detection methods, and in [9] we saw the incorporation of level-set and the geometric active contour framework.

The hybrid and multilevel segmentation technique here presented is aimed at producing accurate and fast segmentation of medical images or any other image with many regions of indistinguishable boundaries. On the first level, it combined region-splitting that was based on multiple threshold with template matching (correlation matching), and on the second level it uses edge based segmentation to find region boundary by discriminating against the adjacent regions.

The rest of the work will be grouped into the following sections. Sections two and three will respectively discuss the hybrid segmentation, and the multilevel segmentation, sections four and five will be on simulation result and discussion, and conclusion and recommendation.

II. HYBRID SEGMENTATION

The idea of hybrid segmentation here refers to the computational implementation of threshold segmentation and correlation matching with region adjacency where correlation matching is unable to categorize a pixel into either of the regions. Multiple threshold points are chosen based on visual information, while the boundaries between regions which are visually indistinguishable are passed onto the correlation matching to resolve, and if required it is further processed by region adjacency.

A. Thresholding

Thresholding is the transformation of an input image (l) to an output (segmented) binary image (B)

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[2], while multiple thresholding is the transformation of an input image (I) into regions of pixels with gray-levels from a set A and otherwise background B. These are represented in the equation (i) to (iv).

$$B(x,y) = \begin{cases} 1 \text{ for } I(x,y) \geq T \text{ (foreground)} \\ 0 \text{ for } I(x,y) < T \text{ (background)} \end{cases} \ldots\ldots\ldots (i)$$

T is threshold, B(x, y) is output pixel, and I(x, y) input pixel intensity value.

$$g(i,j) = \begin{cases} 1 \text{ for } f(i,j) \in A \\ 0 \text{ for } f(i,j) \in B \end{cases} \ldots\ldots\ldots (ii)$$

Since A is a set we divide A into n subsets as:

$$A = \bigcup_{i=1}^{n} A_i \ldots\ldots\ldots (iii)$$

Such that equation (iv) becomes;

$$g(i,j) = \begin{cases} 1 \text{ for } f(i,j) \in A_1 \\ 2 \text{ for } f(i,j) \in A_2 \\ 3 \text{ for } f(i,j) \in A_3 \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ n \text{ for } f(i,j) \in A_n \\ 0 \text{ for } f(i,j) \in B \end{cases} \ldots\ldots\ldots (iv)$$

Thus equation (iv) represents multiple thresholding as depicted in figure 1.

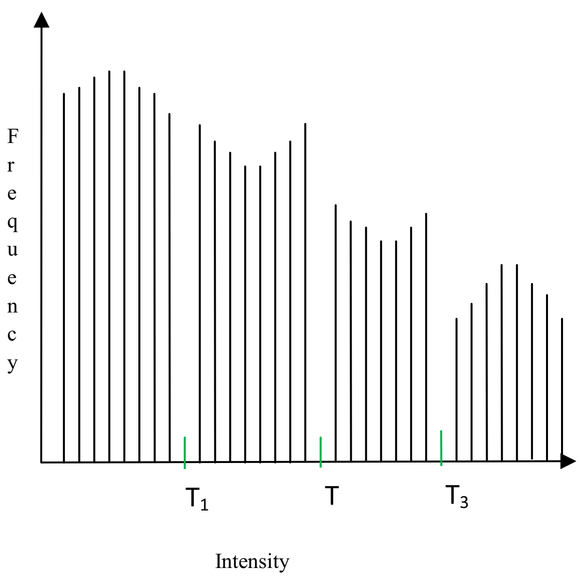

Fig. 1. Multiple Thresholding graph

B. Correlation Matching

Correlation is a linear and shift-invariant mathematically operation used in signal and image processing for extraction of information from signals and images. One of the simplest ways to use correlation for information extraction from an image is to pass the image template across a filter of known characteristics, and perform a linear and shift-invariant correlation operation. One would observe that where the image template matches well with the filter, these are the places of high correlation.

A mathematical proof of this is stated in finding the Euclidean distance between the filter and the image template as represented in the equation (v)

$$\sum_{i=-N}^{N} (F(i) - I(x+i))^2 = \sum_{i=-N}^{N} \left(F^2(i) + I^2(x+i) - 2F(i)I(x+i)\right)$$
$$= \sum_{i=-N}^{N} (F^2(i)) + \sum_{i=-N}^{N} (I^2(x+i)) - 2\sum_{i=-N}^{N} (F(i)I(x+i)) \ldots\ldots (v)$$

The image template is the portion of the image centered at x represented by $I(x+i)$ to be correlated with the filter $F(i)$. The first part of equation (v) depends on the filter, the sum of the square of pixel value that overlap the filter formed the second part, and negated magnitude that is twice the correlation between image and filter forms the third part. The Euclidean distance between the image and filter decreases as the correlation by the two increases. This is the approach applied in this work except that a 2D (3-by-3) filter is constructed around a single image pixel and this is correlated with the boundary pixels of the regions bordering the image pixel. A basic equation for a square filter is given in equation (iv)

$$FcorrI(x,y) = \sum_{j=-N}^{N} \sum_{i=-N}^{N} F(i,j) I(x+i, y+j) \ldots\ldots\ldots (vi)$$

Our approach is that 3-by-3 filters are formed around a pixel of interest (P) while the two threshold valued pixels represent the visual limits of two adjacent regions are used successively to correlate the 3-by-3 filter. The sum of the square of difference between each element of the filter and each boundary pixels are formed. The two numbers are compared and the bigger belongs to the region that produces it.

$$PFcorrI_1 = \sum_{j=1}^{3} \sum_{i=1}^{3} (PF(i,j) - I_1)^2 \ldots\ldots\ldots (vii)$$

$$PFcorrI_2 = \sum_{j=1}^{8}\sum_{i=1}^{8}(PF(i) - I_2)^2 \ldots\ldots\ldots(viii)$$

Having found the correlation for the two boundary values, if $PFcorrI_1$ is greater than $PFcorrI_2$, pixel P belongs to region I_1, and if $PFcorrI_2$ is greater, pixel P belongs to region I_2. However, if the two are equal in magnitude, the distance between pixel P and pixels I_1 and I_2 are measured, then, pixel P is made part of the region where a shorter distance is measured.

III. MULTILEVEL SEGMENTATION

Medical image data is ambiguous with intensity based segmentation like thresholding because several organs share the same intensity range. The problem is solved by making the output of the hybrid stage, that is, thresholding and correlation matching, to be the input to the next phase of segmentation. In this work, the next higher stage processing is edge detection, an edge is a set of connected pixels that lie on the boundary between two regions [10]. We accomplished this by first isolating the region of interest (ROI) and then find the edge of the brain tumor by processing the region using MATLAB (in grid environment) to find the pixels that lied in the boundary.

For instance, if R2 is a subset of the main set (brain slice), consisting of one or more tumor locations plus other anatomical structures that have same intensity as tumor cells, and fluid paths, then the region of interest ROI will be a subset of R2 consisting of a tumor location and its neighbouring anatomical structure of different intensities. This could be represented as:

BS = {R1, R2, R3, R4} ………(ix)

R2 ⊂ BS, and

R2 = {Ts, Fv, O} ………(x)

R1, R2, R3, and R4 are used to represent regions of different anatomical structures in the brain slice (BS) namely bones, tumor, normal brain cells, and fluids. In the subset R2 we have a number of isolated tumors Ts (if we are dealing with patient of multi-site tumor), fluid vessels Fv, and other structures that exhibit similar intensity as the brain tumor. Hence, isolating only tumors (Ts) or one of the tumors is our ROI.

IV. SEGMENTATION RESULTS AND DISCUSSION

All the above procedures were codified in MATLAB programming language and simulated. In spite of the fact that work is still on-going to perfect the code for better result, our early results show a promising trend, and are here presented in figures 2 to 4.

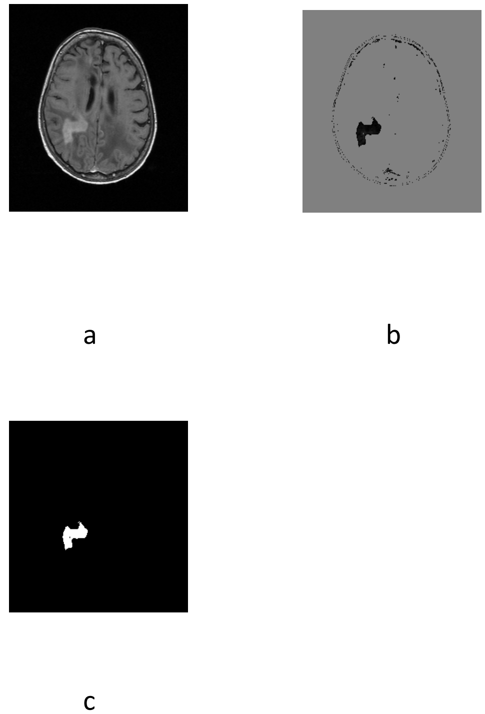

Fig. 2. (a) original image with only one tumor location, (b) result of hybrid stage, and (c) result of second stage processing

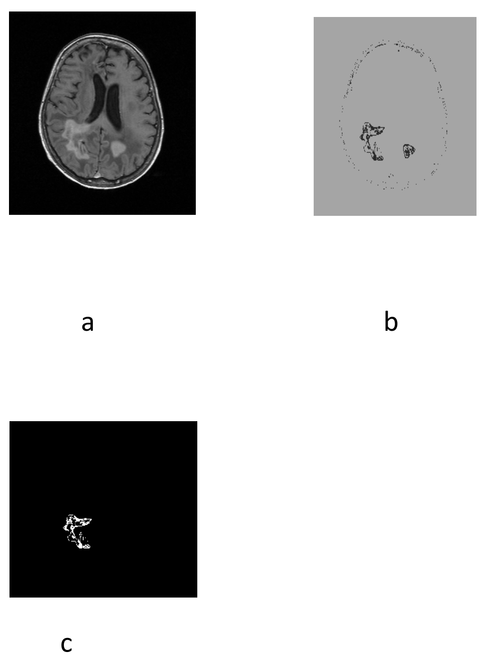

Fig. 3. (a) original image with two tumor locations, (b) result of hybrid stage, and (c) result of second stage processing

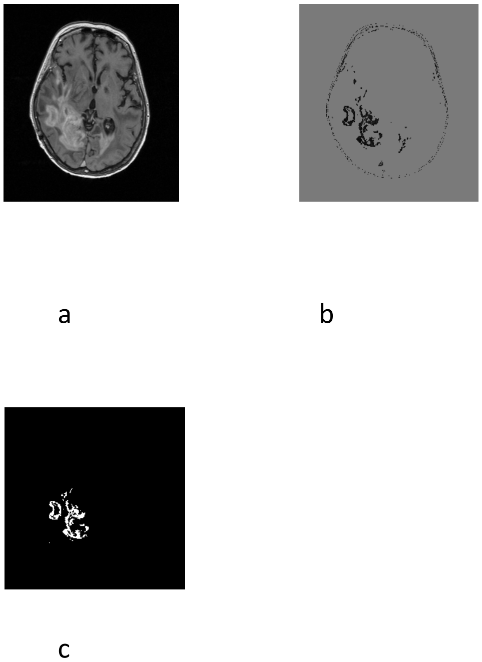

Fig. 4. (a) original image with multiple tumor locations, (b) result of hybrid stage, and (c) result of second stage processing

Figures 2 to 4 represent the initial result of hybrid and multilevel processing of medical images for better analysis of ROI. The result shows the powers of the process, the (b) parts of figure 2 to 4 present its ability to isolate areas with similar intensity and extend the boundaries of the two regions, and at the second phase it is able to further isolate and process any part that is of our main interest. In the cases above, figure 2a has only one tumor location, hence figure 2c has only one location. As for figure 3a, it has two tumor locations and we are able to extract one as shown in figure 3c, while figure 4a has lots of disjointed tumors and we targeted some for final segmentation as shown in figure 4c.

V. Conclusion And Recommendation

It has been shown that an accurate and fast segmentation of medical images is possible with our hybrid and multilevel segmentation technique based on the preliminary results. Since the work is still on-going, better results will be presented in the near future and an extension of the analysis at the second phase to find the size of tumor in our region of interest (ROI).

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