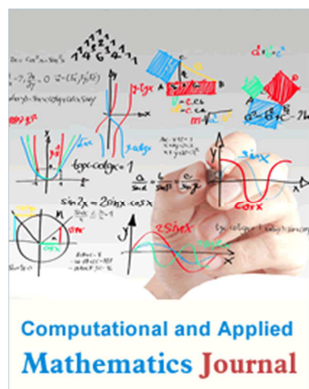




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Region and Active Contour-Based Segmentation Technique for Medical and Weak-Edged Images

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Abstract

One of the key requirement in image guided surgery (IGS)/ computer aided surgery (CAS) planning is accurate segmentation of the images concerned. It is also a challenging issue for the purpose of image analysis and understanding in general, and surgical intervention involving image guided surgery (IGS) in particular. Thus, in this paper, a technique employing two-stage segmentation in which one of the stage is also an hybrid of two segmentation methods is developed for medical images in particular, and weak-edged images in general. The first stage employs hybrid of multiple-thresholding and correlation matching. The output image of the first stage was use as the input image to the second stage to generate the final output using the modified Chan-Vese level-set algorithm (MLSA). The results obtained is accurate as showed in figures 2, 3, and 4.

1. Introduction

Image segmentation is one of most important steps leading to analysis and understanding of processed image data. Its main goal is to divide image into parts that have a strong correlation with objects or areas of the real world contained in the image [1], [2] or segments that are intelligently distinguishable. Segmentation using energy functional called level-set algorithm was carried out by [3], it is a good and fast segmentation technique especially if the regions in the image are distinguishable to some extent. The work in [4] used the hybrid of edge detection and region-growing to achieve better segmentation result. Construction of brain atlas from images obtained from MRI using some Chinese people as experiment was carried out by [5]. Combinations of several methods which include spatial normalization using statistical parametric mapping, Gaussian smoothing, and non-linear transformation were step wisely applied on the MRI images. A 3D-structure digitalized Atlas of Chinese Brain was established with more work left to be done on making the cerebral region clearer. The research of [6] explored the development of a new technique for localizing small pulmonary nodules (lump) before thoracoscopic (related to chest) surgery using image guided navigation system. Using animals for experiment, lesions were created with a mixture of oily radiographic contrast and tissue adhesive was percutaneously placed under fluoroscopic guidance through a 22 gauge. The result is that all lesions were successfully localized in the thoracoscope image, and all resection margins were microscopically clear as confirmed

by the pathology examination. There were no surgical complications and the work's major limitation was that the movement of diaphragm and chest wall during respiration affected the accuracy of localization.

Furthermore, the hybrid of local geodesic active contours and a more global region-based active contour was presented in [7]. The resulting technique is more versatile than either of the two methods that produced it owing to its robustness to noise and reduced dependency on initial curve placement. [8] hybridized region growing method and edge detection method as a way of getting better result. Initial results are promising but further work is still on-going. In [9] a successful segmentation result was obtained using level-set where energy model based on the metric was incorporated into the geometric active contour framework. Finally, a self-learning, and fully automatic segmentation technique was realized based on the use of adaptive region-growing method by [10]. Like the work of [3], it allows region-specific variation of the homogeneity criterion. Furthermore, [11] segmented occluded, cluttered, and noisy images by conditioning the zero level-set curve to stop based on prior shape. This approach is not able to segment many object simultaneously but good at single object segmentation.

The research by [12] is such that the use of Quantum Dot of targeted tumor was investigated as a way of helping surgeons to find tumor boundary. Also, it was seen in [13] where an evaluation of interstitial microwave probe as a means of estimating the boundary of tumor was conducted. Of equal interest is the use of sparse finite element to enhance level-set algorithm by [14] which has resulted in good and faster segmentation as compared with Chan-Vese level-set algorithm but limited to 2D images unlike its improved version by [15] that in addition to having 3D capability, it is equally fast like its predecessor.

Nonetheless, as shown by the review of segmentation methods, no segmentation method is perfect for all types of images [16], and most often, combination of two or more methods are required to attain accurate segmentation result as was reported in [17], and expanded upon in the current work.

Medical images like all other weak-edge images are difficult to perfectly segment. In spite of numerous advantages of Image guided surgery (IGS) over the traditional more invasive method of surgical operation, incomplete ablation or over-resection due to improper segmentation has been known to be the likely outcome of surgical intervention involving brain tumor removal. The implication of these is either tumor recurrence or damage to healthy tissues. With about 95% of tumor recurrence close to the primary site of initial resection, the author believes that with accurate segmentation, precise tumor resection would be possible. Hence, in this paper, the hybrid and bi-level image segmentation technique useful for weak-edge and medical image segmentation with high accuracy is presented.

2. Methodology

Using figure 1 (Magnetic Resonance Image (MRI) of

human brain) as the image in question whose anatomies are to be individually isolated, the authors started the process by visually classifying the brain anatomy into four distinct groups namely; bright anatomy, light anatomy, grey anatomy, and dark anatomy. Table 1 shows the class of different anatomical object contained in figure 1. From these groups the initial minimums and maximums are selected via mouse operation. Then the technique which consists of two (2) steps namely: Hybrid Segmentation; and Modified Level set Algorithm (MLSA) begins. MLSA is occasioned by the absence of the parameter representing the mean intensity of pixels external to the zero level-set curves, and the replacement of grey scale image with the output of the hybrid segmentation (first phase segmentation) stage called 'transformed image'.

3. Visual Classification of Brain Anatomy

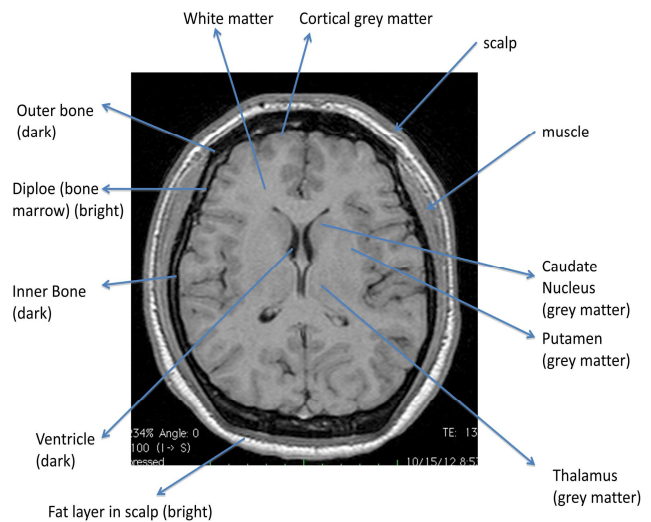


Fig 1a

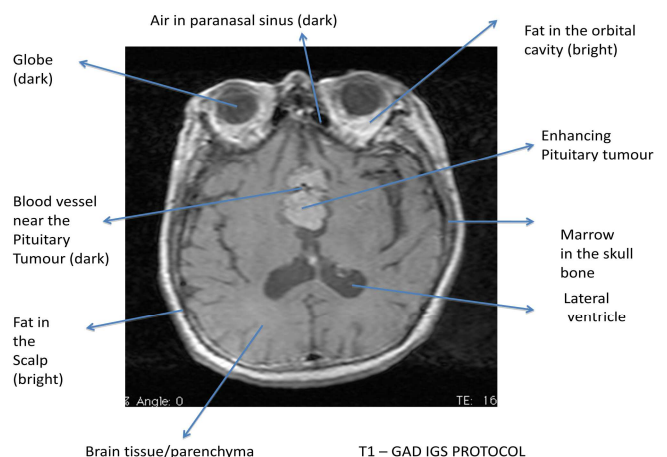


Fig 1b

Fig. 1a and 1b. A typical Human Brain with Anatomical label

Figure 1 is the visual classification of brain MRI protocol image and in Table 1 the classification is grouped and

tabulated according to the visual classification.

Table 1. Classification of Anatomical Structure Appearances in IGS Protocol MRI slice of the Brain

S.No/ Appearance	Bright (Bgt)	Light (Lgt)	Grey (Gry)	Dark (Drk)
1	Fat layer in Scalp	White Matter/ Nerve Fibers (substantia alba) (a)Corpus Callosum (b)Internal Capsule	Grey Matter/ Cell Bodies (Substantia Grisea) (a) Cortical (b)Caudate Nucleus (c)Putamen (d)Thalamus (e)Insula (f)Periaqueductal	Ventricle
2	Bone Marrow	Tumor	Muscle	Inner Bone
3			Scalp	Outer Bone

4. The Bi-Level Segmentation Technique

The technique comprises of hybrid segmentation (intelligent combination of multiple thresholding and 2D template matching) as the first phase of the segmentation process, which could be classified as basic image segmentation. The second phase of segmentation which is related to advanced image segmentation uses active contour-based segmentation called modified level-set algorithm (MLSA) resulting from chan-vese level-set algorithm (LSA). This is a two phase segmentation plan in which the outputs of the first phase called binary space (BS) transform image is used as input to the second phase. This enables proper isolation of region of interest (ROI) and enhances good guidance during surgical planning and intervention. Thus, it implies separation of the four classes of anatomy in table (1) into individual group or regions on separate but same intensity background (black). Thus, equation (1) is a set of all element of IGS protocol image, and equation (2) is an expression of the image intended at the end of the hybrid and bi-level segmentation technique.

$$G = \{B, B_{gt}, L_{gt}, G_{ry}, D_{rk}\} \quad (1)$$

where G is the set of all anatomy of IGS protocol image, B is the black background, and $B_{gt}, L_{gt}, G_{ry}, D_{rk}$ respectively stands for bright anatomy, light anatomy, grey anatomy, and dark anatomy as labeled in figure 1, and $g(i,j)$ represents an element of the anatomical class in table 1.

$$g(i,j) = \begin{cases} 1 & \text{for } (i,j) \in B_{gt} \\ 2 & \text{for } (i,j) \in L_{gt} \\ 3 & \text{for } (i,j) \in G_{ry} \\ 4 & \text{for } (i,j) \in D_{rk} \\ 0 & \text{for } (i,j) \in B \end{cases} \quad (2)$$

If the intensity for normal brain tissue giving as G_{ry} in equation (2) is separated on a uniform background, using region of interest (ROI) processing, its boundary could be determined during the second phase of the segmentation that uses MLSA. The goal of the first phase processing is to have an image represented by equation (3).

$$G_{Gry} = \{B, G_{ry}\} \quad (3)$$

The formulation of mathematical analogy that enables this then follows:

4.1. Formulating the Model for Boundary Pixels

In this paper, only the bright, light, and grey anatomies will be identified and processed leaving-out the dark anatomy in order to reduce computational workload since the anatomy of interest is tumor designated as light anatomy (Lgt) which is embedded in-between the bright (Bgt) and grey (Gry) anatomies. Hence, the background and the dark anatomy are assumed same leaving us with an image comprising of four regions namely bright, light, and grey anatomies, and the background assigned A, B, C, and D. Medical images being weak-edge images, the first step is to determine the number of threshold points and intercepts areas for a given image, and this is related by equations (4) and (5).

$$\mu\mu = 2\tau - 2 \quad (4)$$

$$\omega = \tau - 1 \quad (5)$$

where τ is the number of regions in an image inclusive of the boundary, $\mu\mu$ is the number of threshold points needed to segment the image into different objects, and ω is the number of intercept points required to segment weak-edge images into different regions that the image is made up of.

According to equations (4) and (5), a weak-edged image with four (4) regions would have six (6) threshold points and three (3) intercepts points. The threshold points designed to be chosen by mouse operation are assigned correspondingly as $A_{min}, B_{max}, B_{min}, C_{max}, C_{min},$ and D_{max} respectively. These are perceivable minimums and maximums in each region while the absolute minimum for regions A, B, and C, and the absolute maximum for regions B, C, and D hang in the intercept regions. Therefore, one of the tasks is to find the three absolute minimum or maximum threshold equations in compliance with the number of intercepts points.

Thus if we denote the six (6) absolute threshold points for the four-region image as: $A_{min_0}, B_{max_0}, B_{min_0}, C_{max_0}, C_{min_0},$ and D_{max_0} respectively, and the intercept points between the regions are labeled as: Intercept of region A

(bright anatomy) and B(light anatomy) as x , Intercept of region B (light anatomy) and C(grey anatomy) as y , and Intercept of region C (grey anatomy) and D (dark anatomy) as z . Therefore the pixels within the intercept regions whose affinity is to be determined are called target pixels (tp) and are separately designated according to their intercepts as xtp , ytp , and ztp respectively. A suitable way is to approach this is intercept by intercept basis. Again within an intercept, the pixels are individually treated as target pixel tp one after the other, where tp ranges from the first tp (tp_1) to the last tp (tp_{last})

In order to determine in which intercept a target pixel belong to, the use of quadrance $quad$ is employed. In this approach, the target pixel inside an intercept is conceptually made the centre between the minimum or maximum thresholds from each of the adjacent regions to the intercept (for instance regions A and B). Thus, the quadrance between the target pixel and the two threshold points are determined, then the infimum inf of two quadrances $quad$ is determined to know which of the thresholds from the adjacent regions shares more affinity with the target pixel tp . Equation (6) is the basic quadrance equation.

$$Quad = (\theta - \rho)^2 \quad (6)$$

where θ stands for a threshold and ρ stands for target pixel tp . Equations (7) and (8) are equations representing array of two quadrances, and infimum of the array for x intercept. xtp_1 represents the first target pixel in the x intercept. A_{min} and B_{max} are the minimum threshold point in region A and maximum threshold point in region B respectively

$$V_x = \{(A_{min} - xtp_1)^2, (B_{max} - xtp_1)^2\} \quad (7)$$

$$I(x) = \inf\{V_x\} \quad (8)$$

Since the objective is to locate a point of similarity between regions of an image and not from one point to another, it is preferable to use a tool for pattern recognition such as correlation matching whose prove for use in pattern recognition is shown in equation (9). More so, equations (6) and (9) are similar as a measure of separation between two point.

$$\sum_{i=-N_s}^{N_s} (F(i) - I(x+i))^2 = \sum_{i=-N_s}^{N_s} (F^2(i) + I^2(x+i) - 2F(i)I(x+i)) \quad (9)$$

In Equation (9) N_s is the size of the array or matrix, image or threshold point is I , and F represents image template or filter or target pixel tp .

4.2. Hybridization of Multiple Thresholding and Correlation Matching

This is the hybridization of multiple thresholding and template matching in which the threshold points are considered images and the target pixels are filters. Furthermore, the immediate neighbours of each threshold

point and target pixel are incorporated into the calculation to form an n by n matrix with the threshold point as the center of the n by n matrix for the image side, and target pixel as the center of the n by n matrix for the filter side respectively. The correlation equation proving the possibility of this operation is given in equation (10) such that $f \otimes g$ is correlation of f and g and the limit is specified on the integral functions (2D correlation)

$$(fg)(\rho, \vartheta) \stackrel{\text{def}}{=} \int_{-\gamma}^{\gamma} \int_{-\epsilon}^{\epsilon} f(\epsilon, \gamma) g(\rho + \epsilon, \vartheta + \gamma) d\epsilon d\gamma \quad (10)$$

Resolving the affinity of each pixel in individual region requires going pixel by pixel, thus if the total number of pixels in each of the intercept (x , y , & z) is numbered from one (1) to l , m , & n , then we shall have l , m , & n numbers of iteration in each intercept before the absolute minimum or maximum would be arrived at. Therefore, the target pixels are labeled xtp_1 to xtp_l , ytp_1 to ytp_m , and ztp_1 to ztp_n respectively. This implies that at the end of every iteration, the chosen minimum or maximum may take on a new value depending on which region the target pixel falls into. This means a new minimum or maximum is computed at the end of every iteration. Thence, given that the initial (mouse operation chosen) minimum and maximum for regions A, B and C are designated as; A_{min}^{α} & B_{max}^{α} , B_{min}^{β} & C_{max}^{β} , and C_{min}^{σ} & D_{max}^{σ} , while the final minimum and maximum for the same regions are; $A_{min}^{\alpha+l}$ & $B_{max}^{\alpha+l}$, $B_{min}^{\beta+m}$ & $C_{max}^{\beta+m}$, and $C_{min}^{\sigma+n}$ & $D_{max}^{\sigma+n}$. The quadrance vector and infimum for the first pixel for each intercept are shown in equations (11) to (16):

$$V_x = \{(A_{min}^{\alpha} - xtp_1)^2, (B_{max}^{\alpha} - xtp_1)^2\} = (A_{xtp}, B_{xtp}) \quad (11)$$

$$I(x) = \inf\{V_x\} \quad (12)$$

$$V_y = \{(B_{min}^{\beta} - ytp_1)^2, (C_{max}^{\beta} - ytp_1)^2\} = (B_{ytp}, C_{ytp}) \quad (13)$$

$$I(y) = \inf\{V_y\} \quad (14)$$

$$V_z = \{(C_{min}^{\sigma} - ztp_1)^2, (D_{max}^{\sigma} - ztp_1)^2\} = (C_{ztp}, D_{ztp}) \quad (15)$$

$$I(z) = \inf\{V_z\} \quad (16)$$

The implementation is such that the center correlation CC between an image (threshold point) and a filter (target pixel) is determined as represented by equation (17). Once equation (17) is applied on two adjacent threshold points, equation (18) is used to find the infimum between the two and equation (19) then places the target pixel to either of the adjacent regions, and instantaneously updates the two concerned thresholds. Equations (19) to (24) are the models for the first and last pixels in each of the intercept regions. In these equations, A_{min}^{α} & B_{max}^{α} are the initial chosen thresholds from adjacent regions A and B, xtp_1 is the first tp in intercept x , and $A_{min}^{\alpha+1}$ & $B_{max}^{\alpha+1}$ are the first updates A_{min}^{α} & B_{max}^{α} after the tp has been classified into either of the regions.

$$CC(A_{xtp}) = (A_{min}^{\alpha})(xtp_1) = (A_{min}^{\alpha}(\pi_0, \varphi_0))(xtp_1) = \sum_{j=-N_m}^{N_m} \sum_{i=-N_m}^{N_m} (xtp_1(i, j) A_{min}^{\alpha}(\pi_0 + i, \varphi_0 + j))^2 \quad (17)$$

$$P(x_l) = \inf\{CC(Axtp_1), CC(Bxtp_1)\} \quad (18)$$

The first infimum calculated from intercept x is:

$$P(x_1) = \begin{cases} CC(Axtp), xtp_1 \in A \text{ then} \\ A_{min}^{\alpha+1} = A_{min}^{\alpha} - (A_{min}^{\alpha} - xtp_1) \text{ and} \\ B_{max}^{\alpha+1} = B_{max}^{\alpha} \\ \\ CC(Bxtp), xtp_1 \in B \text{ then} \\ B_{max}^{\alpha+1} = B_{max}^{\alpha} + (xtp_1 - B_{max}^{\alpha}) \text{ and} \\ A_{min}^{\alpha+1} = A_{min}^{\alpha} \end{cases} \quad (19)$$

$$P(z_n) = \begin{cases} CC(Cztp), ztp_n \in C \text{ then} \\ C_{min}^{\sigma+n} = C_{min}^{\sigma+n-1} - (C_{min}^{\sigma+n-1} - n) \text{ and} \\ D_{max}^{\sigma+n} = D_{max}^{\sigma+n-1} \\ \\ CC(Dztp), ztp_m \in D \text{ then} \\ D_{max}^{\sigma+n} = D_{max}^{\sigma+n-1} + (ztp_n - D_{max}^{\sigma+n-1}) \text{ and} \\ C_{min}^{\sigma+n} = C_{min}^{\sigma+n-1} \end{cases} \quad (24)$$

And for the last xtp called xtp_l , the last infimum called $\inf x_l$ is given by:

$$P(x_l) = \begin{cases} CC(Axtp), xtp_l \in A \text{ then} \\ A_{min}^{\alpha+l} = A_{min}^{\alpha+l-1} - (A_{min}^{\alpha+l-1} - xtp_l) \text{ and} \\ B_{max}^{\alpha+l} = B_{max}^{\alpha+l-1} \\ \\ CC(Bxtp), xtp_l \in B \text{ then} \\ B_{max}^{\alpha+l} = B_{max}^{\alpha+l-1} + (xtp_l - B_{max}^{\alpha+l-1}) \text{ and} \\ A_{min}^{\alpha+l} = A_{min}^{\alpha+l-1} \end{cases} \quad (20)$$

Likewise, the first infimum calculated from intercept y is:

$$P(y_1) = \begin{cases} CC(Bytp), ytp_1 \in B \text{ then} \\ B_{min}^{\beta+1} = B_{min}^{\beta} - (B_{min}^{\beta} - ytp_1) \text{ and} \\ C_{max}^{\beta+1} = C_{max}^{\beta} \\ \\ CC(Cytp), ytp_1 \in C \text{ then} \\ C_{max}^{\beta+1} = C_{max}^{\beta} + (ytp_1 - C_{max}^{\beta}) \text{ and} \\ B_{min}^{\beta+1} = B_{min}^{\beta} \end{cases} \quad (21)$$

And its last infimum is:

$$P(y_m) = \begin{cases} CC(Bytp), ytp_m \in B \text{ then} \\ B_{min}^{\beta+m} = B_{min}^{\beta+m-1} - (B_{min}^{\beta+m-1} - ytp_m) \text{ and} \\ C_{max}^{\beta+m} = C_{max}^{\beta+m-1} \\ \\ CC(Cytp), ytp_m \in C \text{ then} \\ C_{max}^{\beta+m} = C_{max}^{\beta+m-1} + (ytp_m - C_{max}^{\beta+m-1}) \text{ and} \\ B_{min}^{\beta+m} = B_{min}^{\beta+m-1} \end{cases} \quad (22)$$

Moreso, from intercept z, first infimum is:

$$P(z_1) = \begin{cases} CC(Cztp), ztp_1 \in C \text{ then} \\ C_{min}^{\sigma+1} = C_{min}^{\sigma} - (C_{min}^{\sigma} - ztp_1) \text{ and} \\ D_{max}^{\sigma+1} = D_{max}^{\sigma} \\ \\ CC(Dztp), ztp_1 \in D \text{ then} \\ D_{max}^{\sigma+1} = D_{max}^{\sigma} + (ztp_1 - D_{max}^{\sigma}) \text{ and} \\ C_{min}^{\sigma+1} = C_{min}^{\sigma} \end{cases} \quad (23)$$

Again the last infimum in intercept z is:

The process continues until the last target pixel in all the intercepts are classified. Hence, the last updates on each of the initial chosen thresholds are the absolute minimums and absolute maximum as shown in equations (25) to (30).

$$Amin_0 = A_{min}^{\alpha+l} \quad (25)$$

$$Bmax_0 = B_{max}^{\alpha+l} \quad (26)$$

$$Bmin_0 = B_{min}^{\beta+m} \quad (27)$$

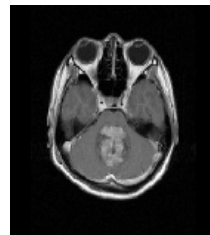
$$Cmax_0 = C_{max}^{\beta+m} \quad (28)$$

$$Cmin_0 = C_{min}^{n+m} \quad (29)$$

$$Dmax_0 = D_{max}^{n+m} \quad (30)$$

Figure 2 is the result obtained when the absolute thresholds are used in the segmentation of an MR axial image (in grayscale) of a human head (top left) into bright anatomy (top right), light anatomy (bottom left), and grey anatomy (bottom right). This operation is reckoned as transformation I^T from the grey-scale (GS) MR image to three different anatomical structures as a consequence of the hybrid segmentation technique. Moreover the anatomy of interest is the tumor found amidst light anatomy L_{gt} noted after transformation as I_l^T (bottom left). This is categorized as first phase segmentation.

MRI Tumorous Brain Slice



Bright Anatomical Structures



Light Anatomical Structures



Grey Anatomical Structures

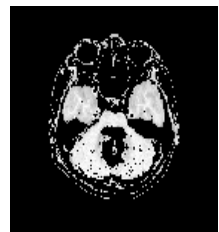


Fig. 2a

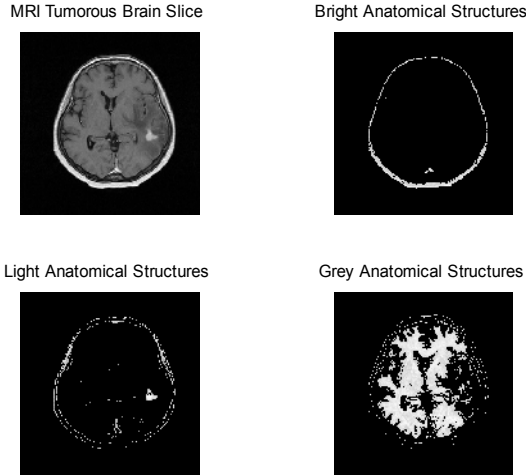


Fig. 2b

Fig. 2a and 2b. Grey scale image (upper left) and the other three anatomical divisions

This transformation is reckoned as I^T , but each one of the transformation images is called binary space (BS) transform image designated as I_b^T , I_l^T , and I_g^T for bright, light, and grey anatomies respectively. This is noted as the first phase of the proposed bi-level segmentation technique.

4.3. The Modified Level-Set Algorithm

The modified level-set algorithm (MLSA) is a modified form of the Chan-Vese (10) energy functional occasioned by the zerolization of the parameter representing the mean intensity of pixels external to the zero level-set curve, and also, the replacement of grey scale image with any of the transformed image, in this case I_l^T . Hence, equations (31) and (32):

$$\phi_{i,j}^{n+1} \left[1 + \frac{\Delta t}{h} \delta_h(\phi_{i,j}^n) \mu (C_1 + C_2 + C_3 + C_4) \right] = \phi_{i,j}^n + \frac{\Delta t}{h} \delta_h(\phi_{i,j}^n) \mu \left[\begin{array}{c} C_1 \phi_{i+1,j}^{n+1} + C_2 \phi_{i-1,j}^{n+1} + C_3 \phi_{i,j+1}^{n+1} + \\ C_4 \phi_{i,j-1}^{n+1} \end{array} \right] - \Delta t \delta_h(\phi_{i,j}^n) \left[\begin{array}{c} v + \lambda_1 (I_{i,j}^T - a_1(\phi^n))^2 - \\ \lambda_2 (I_{i,j}^T)^2 \end{array} \right] \quad (31)$$

$$p_{i,j} = \phi_{i,j}^n - \Delta t \delta_h(\phi_{i,j}^n) \left[v + \lambda_1 (I_{i,j}^T - a_1(\phi^n))^2 - \lambda_2 (I_{i,j}^T)^2 \right] \quad (32)$$

in which $\phi_{i,j}^n$ stands for the value of ϕ at pixel i, j and at n iteration, Δt is the time step, smoothed version of the Dirac function δ is here represented by δ_h , pixel spacing h . Also μ (length of level-set curve), v (area of level-set curve), λ_1 (inner uniformity factor), and λ_2 (outer uniformity factor). a_1 represents the mean intensities of the interior of the level-set curve $C(\phi)$, and $I_{i,j}^T$ is the transform image representing light anatomical structure. μ , v , λ_1 , and λ_2 are ≥ 0

$C_1 = C_1 \phi_{i+1,j}^{n+1}$ - value of ϕ by next iteration ($n+1$) at next row ($i+1$)

$C_2 = C_2 \phi_{i-1,j}^{n+1}$ - value of ϕ by next iteration ($n+1$) at previous row ($i-1$)

$C_3 = C_3 \phi_{i,j+1}^{n+1}$ - value of ϕ by next iteration ($n+1$) at next column ($j+1$)

$C_4 = C_4 \phi_{i,j-1}^{n+1}$ - value of ϕ by next iteration ($n+1$) at previous column ($j-1$)

Equations (31) and (32) being modified form of Chan-Vese energy functional hence, the name; Modified Level-set Algorithm (MLSA) which operates only on any of the binary space transformed (BST) image I^T . The MLSA is noted the second phase segmentation to produce a final image which is an encirclement of the region of interest (ROI). A typical output image of this stage is in figure 3 which shows the transformation from GS image (top left) to Light anatomy image (top right) from first phase segmentation to second phase segmentation in which tumor edge is accurately encircled in red (bottom left), and the segment without

outline (bottom right).

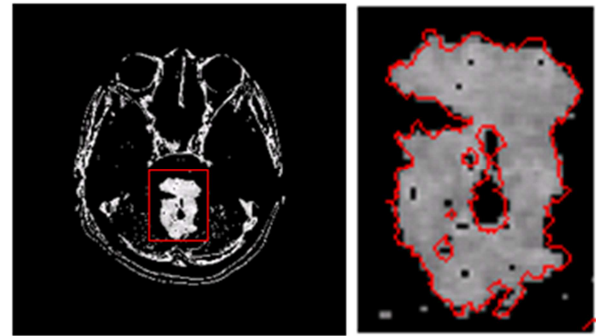


Fig. 3a

Fig. 3b

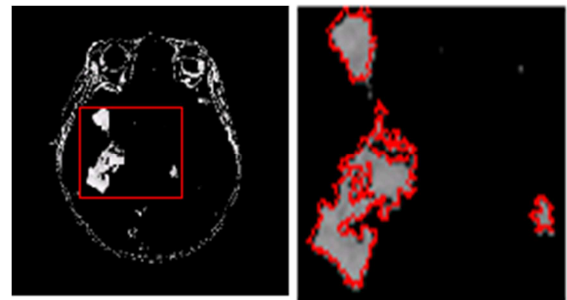


Fig. 4a

Fig. 4b

Fig. 3 and 4. (a) Light anatomy image enclosed in zero-level-set and (b) output of Modified LSA

5. Summary

The novel hybrid segmentation for weak edge images in general and medical images in particular is presented. It begins with visual classification of brain anatomy in bright, light, grey, and dark anatomies which led to the determination of number of possible threshold points and intercept regions such division would have. Having done that, initial threshold points are picked by a human user, which are then automatically compared with individual pixels (called target pixels) within the intercept regions to determine which of the two thresholds the pixel is closer to. It is at that point of comparison that the authors decided to change the approach to using 2D correlation matching for it proven record in image segmentation instead of mare quadrance and infimum/supremum. The pixel information is used in continuous update of initial threshold points until an absolute threshold for each of the region is achieved. The absolute thresholds are then use to segment the grey scale image into the desired four anatomical groups.

6. Conclusion

The results obtained showed high accuracy and could be extended to include the use of active contour like level-set algorithm for proper boundary definition. It could also be useful in volume quantification for purposes of surgical intervention.

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