Novel Seed Selection and Conceptual Region Growing Framework for Medical Image Segmentation

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Abstract

The objective of the paper is to propose a novel idea to improve initial conditions of seeded region growing (SRG) algorithm. We also propose a conceptual region growing framework to contribute to its progress in medical imaging. Our scheme is based on the simple observation that nature seems random but it repeats itself. Medical images are a kind of natural images and hence they must have a tendency of behaving like fractals. Our non-parametric Polygonal Seed Selection method does not need density estimation as before and shows clear Improvement to handle over segmentation problem. Qualitative results have been demonstrated on Axial Slices of Brain using traditional SRG, K-Means and Watershed segmentation.

Keywords: Region growing; K-Means; Watershed image segmentation; Brain Axial Slices.

1. Introduction

Regions in medical images are irregular in shape with least separation between desired and adjacent regions of interest (ROI), the boundaries of ROI are irregular, the gradient strength is weak and more importantly, to follow natural boundaries is an obligation. Region-Based Image Segmentation technique has a tendency to unify or merge pixels on the basis of the *Gestalt law of Similarity and the Gestalt law of Proximity* (Desolneux, Lionel, & Michel, 2006). According to the law of Similarity, "*human cognitive process tends to group similar pixels into regions. This similarity is mostly in the form of color, size, brightness or texture*". The Law of Proximity states that "*neighborhood pixel elements influence the human mind to perceive a region as an appropriate segment*". Region growing works on the same philosophy and group similar pixels together to form a region which may or may not represent a meaningful segment. We, in this paper, want to keep our focus on *region growing* which is significant to segment various medical and natural images. The automation of region growing for full volumetric segmentation seems difficult (rare example exists) and it is frequently employed to segment an object (or organ in case of medical images) rather than entire scan or scene having numerous objects. We hypothesize that various clustering and classification algorithms including superpixel and K-Means are recent variants of classical region growing approaches (Jiayin L., Zhenmin T., Ying C. & Guoxing W 2017) (Achanta & Radhakrishna et. al, 2012) (Aqil, B., & Humera, T. 2014). Under our hypothesis; region growing simply means grouping pixels whether it happens in spatial space or high dimensional feature space or we make it happen by backpropagation learning (Christian F., Lisa M., Kerem C., Jia X., Ender K. 2018). The required computational power of machine will arise a big question mark on our assumption and hypothesis. The most important aspect of the all-region growing algorithm is *Homogeneity criterion or predicate* in the form of some goodness of fit test along with choice of appropriate *data structure* and *evaluation metric*. The significance of region growing technique strongly reflects from its availability in almost all commercially and research purpose brain segmentation for example in ANALYZE (a commercially available segmentation software developed by Mayo foundation (Thatcher, Hallet, Zeffiro, John, & Huerta, 1994). The rest of the paper is organized as follows: In Section I, we reviewed recent region growing literature to identify its application along with imaging modality and predicate. Section 2 discusses the Seeded Region Growing Algorithm to explicate the importance of initial conditions for meaningful segementation. Section 3 reviews the classical literature of similarity based region growing, while section 4 covers the old hybrids and variants of region growing. Section 5 discusses the schematics of region growing pipeline which can be mapped onto recent clustering algorithms. which because different hybrids, extensions and variants of classical regions growing algorithm.

2. Regions Growing for Medical Image Segmentation

Thorough Literature review shows that region growing is an integral technique especially when it comes to medical imaging and usually needs an initial global rough segmentation to start with (Otsu, N., 1979) (Tariq.H, Muqeet.A & et.al 2017). The process may also need the support of post-processing region merging stage to refine segmentation results as indicated by a recent paper on Early detection of breast cancer (Ehsan. K, Mohsen.S, Hamid. B & et. al 2017). They used region growing at first stage and later on, the level set method is employed for final segmentation. This means that complete region growing segmentation needs both syntactic and semantics to work on and is usually a 2 or 3 stage process. Applications of region growing in medical imaging range from X-Ray to ultrasound and to brain MR images for lesion segmentation, cortex (gray matter) segmentation, skull stripping, early detection of cáncer and for various volumetric measurements. A recent example of region growing importance is hippocampus segmentation (Xiaoliang J. and et. al, 2017). Another recent work is multispectral adaptive region growing algorithm (MARGA) (Roura, et al., 2014). This work is an extension to the previous method for skull stripping (Park & Lee, 2009) in support with histogram analysis and morphological operation. A similar work used BRASS (Brain Registration and automated SPECT semi quantification) to perform voxel-wise comparison and is also based on region growing of voxels/pixels (Van Laere, et al., 2002). An adaptive region growing algorithm was proposed in (Modayur, Prothero, Ojemann, Maravilla, & Brinkley, 1997). They employ region growing to extract cortex (i.e. gray matter) from brain volume with the help of growing region based ROI masks. The algorithm keeps on adding pixel/voxels to the region until its size becomes significant which is identified when gray level distribution approaches its true mean. The homogeneity criterion used in an adaptive region growing is as follows:

$$M(x) = \left[\frac{1}{T_r}\frac{(f(x)-\mu_R)^2}{\sigma_R^2}w + \frac{\sigma_N^2}{T_N}(1-w)\right] \leq 1 \qquad (*)$$

Where $f(x) = \ current\ \ pixel\ or\ voxel\ intensity$

$T_R = Threhsold\ for\ region\ R$;

$T_N\ = Threshold\ for\ neighborhood\ N$

$$\mu_R = mean\ intensity\ of\ Region\ R$$

$$\sigma_R^2 = \sqrt{var\{f(x)|\ x \in R\}} \quad ; \quad \sigma_N^2 = \sqrt{var\{f(x)|\exists x' \in N(x): x' \in R\}}$$

$$w = w(|R|) \qquad 0 < w < 1 \qquad T_R, T_N > 0\ \ thresholds\ for\ enlarging\ R$$

(Modayur, Prothero, Ojemann, Maravilla, & Brinkley, 1997) basically, think about two states of a region: when a region is small we say it is purely homogenous and thus $w = 0$ but when the region size is gradually increasing its homogeneity is affected due to joining of more and more neighbor pixels and thus w starts heading towards its second extreme i.e. $w = 1$ showing that region is in deviation state. Thus in the start = 0 , when the grown region doesn't have enough voxels in region i.e. $n_R < n_v$. The maximum value that w can attain is p showing maximum cost. They build 26-adjacent neighborhood N and assume that at least one voxel amongst N must grow region R. The weighting factor w depends on three inputs: predefined minimum voxel count n_v, window voxel count n_{window} and a predefined percentage p. Thus w is defined as follows:

$$w = \begin{cases} 0 \ \ if \ \ n_R < n_v \\ p\left(\frac{n_R - n_v}{n_{window}}\right) if\ n_v \leq n_R \leq (n_v + n_{window}) \\ p \end{cases} \quad (**)$$

Another adaptive region growing algorithm is presented for the extraction of a specific region on the CT image of Liver (Regina & Klaus, 2001). In the first run of this algorithm the values of mean and upper and lower limits of standard deviation are estimated from a 3x3 window around seed pixel. These estimated region characteristics are homogeneity parameters to be used in the second run of the adaptive region growing algorithm. The same seed is then allowed to grow region having n pixels and a lower and upper threshold is computed as follows:

$$T_{lower,upper} = \mu \pm [w\sigma + c(n)] \qquad (1)$$

Where weight $w = 1.5$ and $(n) = {}^{20}/_{\sqrt{n}}$. The rationale behind choosing these values is to include 86% of a pixel in the region assuming the gray level follows from a normal distribution. $c(n)$ needed at an early stage of the growing process and decreases rapidly as region size increases. The extension of this approach to fully automatic segmentation is also demonstrated in the paper. (Zheng, Jesse, & Hugues, 2000) presented a strong concept of unseeded region growing (URG) which do not depends on user input for seed selection rather it searches for the best global pixel for segmentation by maintaining the binary tree (splay queue and heap) of all candidate voxels/pixels of the growing region. The whole process comprises three steps: (1) Perform a binary search to find the set of best candidate pixels for each region. To accomplish this step; a binary tree of gray level is formed along with FIFO queue at each node to hold pixels having the same gray level. (2) Evaluate the δ values of pixels, insert them in a global priority queue with respect to δ values and select the one having mínimum δ. (3) Remove the best pixel from the priority queue and start growing a region. Update region statistics and also add the neighbors of the best pixel to a regional queue. (Zheng, Jesse, & Hugues, 2000) showed segmentation result on X-ray angiogram and heart ultrasound image but no algorithm or pseudo code for URG is presented in the paper. Some of these work is summarized in Table 1. Automation process of region growing is been an area that needs more attention (Chantol & Michel, 1997) (Haralick & Shapiro, 1985) (Zucker, 1976) (Adams & Bischof, 1994). To automate region growing algorithm clearly means the automation of seed selection procedure. A full-length description of automatic region growing is presented in (Chantal, Francoise, Yannick, & Christophe, 2002) for 3D images. This work is an extension of (Chantol & Michel, 1997) in which special dilation operations are used to grow regions with minimum variance, but even in (Chantol & Michel, 1997) work tuning of homogeneity threshold is required.

A distinctive attribute of this work is the segmentation of non-connected regions and in contrast to another region growing algorithm, it is possible that the growing region does not contain initial seed. The idea in the parametric region growing is to build a sequence of growing regions by varying maximal homogeneity threshold σ_{max} which is the standard deviation of the region. Different values of σ_{max} depends on σ_{mean} which is the average of standard deviation taken over initial seed pixels and their neighbors as follows:

$$\sigma_{mean} = \frac{\sum_{i=0}^{N_s} \sigma_{s_i}}{N_s} \tag{2}$$

Table 1. Region growing in Medical Imaging Literature

Algorithm, Year and Author	Similarity Criterion	Image Type/Modality	Application
Adaptive Region Growing and Thresholding, 2017,	Image statistics and DICE coefficient	3D Breast Ultrasound	Early Detection to Breast Cancer
Region growing and Level set, 2017, Xiaoliang J. and et. al.	Standard deviation based on Quadtree decomposition	Brain MR images	Hippocampus segmentation
MARGA: multispectral adaptive region growing algorithm, 2014.Roura et al.	Region statistics	Brain MR images	Skull Stripping
Region growing, 2009. JG Park and C.Lee	Region statistics	Brain MR images	Skull Stripping
Automatic 3D region growing algorithm based on an assessment function, 2002. Chantol Revol-Muller et al.	Dilation transformation based homogeneity criterion Quality assessment function	Volumetric brain images	Application to multimodal histograms.
Unseeded Region Growing. Zheng Lin, Jesse Jin, Hugues Talbot, 2001.	Mean of growing region	X-ray angiogram, heart ultrasound.	Extension to multispectral images.
Adaptive Region growing, 2001.Regina Pohe, Klaus D. Toennies	Regions statistics	Liver CT images	Application to CT images of abdomen and brain MR images.

Once σ_{mean} is obtained the minimum and maximum bound on σ_{max} are given as:

$$\sigma_{min} = (1-\beta)\sigma_{mean} \qquad \text{and} \qquad \sigma_{max} = (1+\beta)\sigma_{mean}$$

(Chantal, Francoise, Yannick, & Christophe, 2002) uses $\beta = 0.5$. For every region, they assess the quality of segmentation and thus find an optimal homogeneity threshold σ_{opt}. The assessment can be done either by boundary based approach or on the basis of region. The boundary based approach is based on a generalization of (Kohler, 1981) and logarithmic image processing (LIP) contrast (Jourlin, Pinoli, & Zeboudj, 1989). The three region based assessment functions include entropy of image $S(\sigma_{max})$ (Kapur, Sahoo, & Wong, 1985) (Pun, 1981), discriminant analysis (Otsu, 1979) (Fukunage, 1972) and stair function (Laboure, 1987). The method was tested on 3D MR images of human calcaneus bone samples to quantify the osteoporosis. (Chantol & Michel, 1997) incorporate the concept of dilation transformation to region growing. The idea was to dilate (expand) a homogenous region R_n by neighborhood N and then to check the homogeneity of expanded region. If the expanded region fails to meet variance based homogeneity criterion voxels/pixels are bumped off (removed) from a region by a process named *contraction* otherwise growing of region continues as in the traditional region growing algorithms. Since at each step some of the extreme voxels (either from the low end of the histogram or from the high end of the histogram) get removed to build a homogenous region of maximal size, the strategy named *the maximum region with minimum varian*ce is used. The Algorithm is listed below:

Maximum Region with Minimum Variance Algorithm (Chantol & Michel, 1997)

$n \leftarrow 1;$
$R_0 \leftarrow \emptyset;$
$R_1 \leftarrow seed;$
WHILE $(R_n \neq R_{n-1})$
  $D_{n+1} \leftarrow R_n \oplus N$ (dilation)
  IF$\left(\sigma_{D_{n+1}} \leq \sigma_{max}\right)$
    $R_{n+1} \leftarrow D_{n+1}$
    $n \leftarrow n+1$
  ELSE
    $D'_{n+1} \leftarrow reduced\ dilation\ of\ D_{n+1}$
    IF $\left(\sigma_{D'_{n+1}} \leq \sigma_{max}\right)$
      $R_{n+1} \leftarrow E(D'_{n+1})$ (extension of D'_{n+1})
      $n \leftarrow n+1$
    ELSE
      $k \leftarrow 1$
      $Max \leftarrow 0;$
      WHILE $(Max = 0)$
        FOR $(i \leftarrow 0) to\ (i = k)$
          $C \leftarrow ith\ k - contraction\ of\ D'_{n+1}$
          IF $\left(\begin{array}{c}(\sigma_C \leq \sigma_{max}) \\ and \\ (Card\ (C) > Max)\end{array}\right)$
            $Max \leftarrow Card\ (C)$
            $R_{n+1} \leftarrow C$
          IF $(Max = 0)$
            $k = k+1$
          ELSE
            $n \leftarrow n+1$

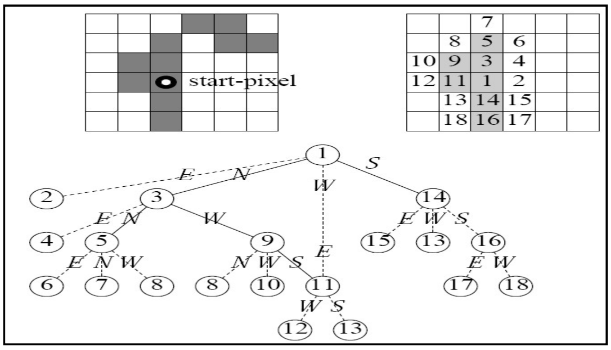


Figure 1. Depth First Traversal (KUNDU, 2011)

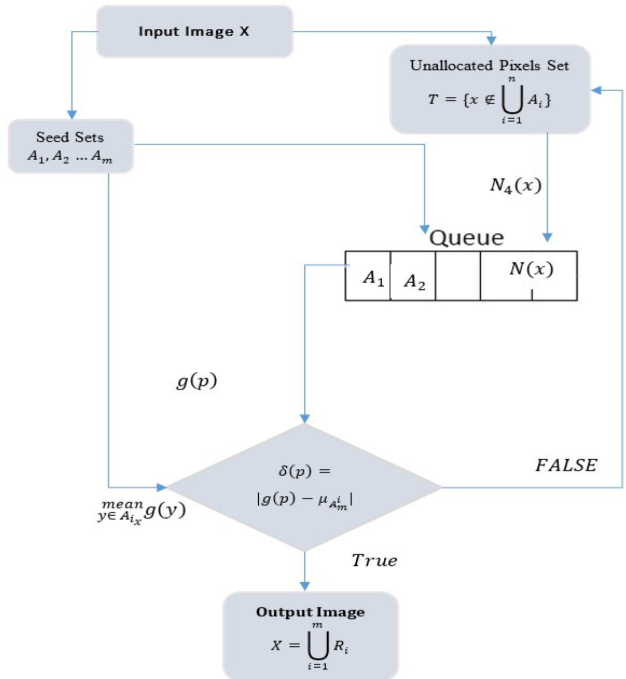


Figure 2. Predicate Mechanism for Non-Parametric SRG

3. Seeded Region Growing (SRG)

The SRG implementation may employ either depth-first or breadth-first traversal. Let's take an arbitrary 6x6 image with single seed pixel. The algorithm starts by visiting neighbors of seeds in a predefined orientation which could be EAST-NORTH-WEST-SOUTH (clockwise ordering) or WEST-SOUTH-EAST-NORTH (anticlockwise ordering). The difference of current pixel's gray level and seed pixel is measured and the decision of inclusion of that pixel into the region is made accordingly. Once a pixel is added, the mean of the region is updated and next neighbor will be chosen for the decision of its inclusion in the region as shown in Figure. 1 and Figure 2. Pixel labeled 1 (seed pixel) has 4-neighbors 2, 3,11, and 14. Since pixel 2 and seed pixel gray level differs entirely; it is analyzed but not labeled neither included in for the growing of region. Such visits need an immediate backtrack during traversal. Let the difference between pixel 3 gray levels and seed pixel gray level is minimum and hence it will be labeled and become part of the growing region, the immediate neighbors of pixel 3 i.e. 4,5 and 9 are analyzed as its neighbor pixel 1 (seed pixel) is already labeled. This time pixel 4 disqualifies for inclusion, pixel 5 qualifies (but its neighbor causes back-tracking), and pixel 9 is also included. This discussion is basically the depth-first labeling approach. Below there is the pseudo code for boundary flagging case as per the original reference of SRG (Adams & Bischof, 1994). This being the most popular and widely used region growing approach. Seeded Region growing algorithm (SRG) starts with the initialization of an image called a seed image $S(x, y)$ of size $M\ X\ N$ usually equal to the image to be segmented (Adams & Bischof, 1994). They determined the seeds for automatic segmentation of human chest X-ray into right lung, left lung and the region between left and right lung in X-ray using converging squares algorithm. The seed image contains 1's at seed pixels' location and is 0 elsewhere. Some natural questions that came into about seed selection are: (1) How many Seeds are enough for good segmentation? (2) What are appropriate seed positions in an image? (3) What is appropriate seed size i.e. 1x1 or 3x3 or 5x5 or 7x7? (4) The seed Selection process is kept automatic or manual? The obvious answer to the first question is: the number of seeds should equal the number of desired regions. Though even a single seed is capable of leading segmentation to distinct regions, provided the regions are homogenous enough with well-separated boundaries, but usually this is not the case. Image data is corrupted by additive and/or multiplicative noise during acquisition causing inhomogeneity or non-uniformity in gray levels. Hence instead of using single small seed, seed areas like 5x5 or 7x7 should be used when segmenting noise images (Adams & Bischof, 1994). This is important because a good starting estimation of the region's mean results in good segmentation. Possible locations of seed pixels are within the region of interest (ROI), on boundaries between regions of interest, within unwanted regions or they may lie within some noisy area of the image. If seed pixel belongs to a region having a uniform gray level, the chances of getting good segmentation increases as SRG gets a stable estimate of region's mean to be segmented. To study the effect of seed position, they perform a test on a comparatively simple image having two uniform regions separated by a broad transition region. They add a low and high level of Gaussian noise and show that a change of seed positions leads to different segmentation results and size of seed matters especially if the noise level is high. For noisy image, large area seeds should be used. The results of SRG segmentation can be improved by means of some splitting or post-processing mechanism in the end if seed position and size is not appropriate in the start. SRG order dependency issue was addressed in Improved Seeded Region Growing abbreviated ISRG (Andrew & Paul, 1997). The order dependency becomes more critical if the image has small regions. First order dependency prevails when a neighbor of seed touches two or more regions and to avoid it such pixels and regions should be handled separately. If the result from first-order dependency causes a tie situation between the candidate pixel and regions, there arises a second order dependency which is handled at post-processing stage.

Classical Seeded Region Growing Algorithm (Adams & Bischof, 1994)

1. **LABEL** Seed Points A_i on a 2D grid as $1,2, \dots \dots \dots n$.
2. **PUT** the neighbors N_8 of A_i into i^{th} data structure (DS) such that $\delta(N_1) > \delta(N_2) > \delta(N_3) > \delta(N_3) \dots \dots \delta(N_8)$
3. **WHILE** (DS is not empty)

   (a)**REMOVE** first pixel p having minimum δ from DS

   (b)**IF** $label(Neighbors(p)))$ **MATCHES** label(A_i)

   SET $label(p) = i$

   UPDATE $mean\ of\ region\ R_i$

   IF $label(Neighbors(p)) == 0\ \&\&\ find(Negibors(P))in\ DS == -1$

   PUT the neighbors N_8 of A_i into i^{th} data structure (DS) such that $\delta(N_1) > \delta(N_2) > \delta(N_3) > \delta(N_3) \dots \dots \delta(N_8)$

   ELSE **FLAG** p with **BOUNDARY_LABEL**

4. Proposed Conceptual Framework

A general two pass seeded region growing (SRG) schematic for image segmentation is conceptualized and proposed with the help of exhaustive literature review The first pass is '*syntactic segmentation*' followed by the second pass named as '*semantic segmentation*'. For images with multimodal histogram (e.g Medical and Natural Images), thresholding or gradients alone are not enough for meaningful segmentation due to broad valleys, overlapping and scattered regions and thus segmentation needs to be guided through appropriate pattern recognition (PR) and/or machine learning technique. Instead of using thresholds at the initial stage to gather global statistics, an alternative is to use edges, preferable close contours, for initial segmentation for which watershed or fuzzy is most appropriate. With a well define seed selection procedure and homogeneity predicate; appropriate feature vectors or feature maps can be prepared which will be mapped to higher dimensional feature space or fed to Neural Network or deep learning network for high-level recognition. We put thresholding, region growing and edge detection under the category of *syntactic segmentation* as these techniques work purely on the basis of pixels gray levels and regional neighbor spatial information. The purpose of threshold segmentation at the very first stage is to gather global information to aid region growing algorithm which works solely on the basis of local and regional properties, most often the pixels /voxels gray levels along with their spatial coordinate information. To overcome the semantic weakness of low and mid-level segmentation algorithms, the extracted regional descriptors (gray levels, texture, size, boundaries, and shapes) from region growing block and/or are passed on to a semantic analysis of objects or scene. This is how true segmentation via region growing mechanism can be achieved. The schematic that we use for region growing segmentation procedure comprises of following steps: (1) Variance Stabilization technique (VST) (2) Global Statistics estimation (3) Seed Selection (4) Predicate Design (5) Region Growing (6) Classification and Labeling and (7) Visualization.

Various options exist for Variance stabilization transformation (VST) transformation depending on the distribution of noise in the degraded image. The most popular are Log Transformation $X \to \log(X)$ and Power transformation $X \to X^{\beta}\ for\ some\ \beta > 0$. The Variance stabilization transformation (VST) is also an important tool to convert non-Gaussian noise into Gaussian one which makes restoration and reconstruction of images convenient for processing. For example, to apply a T-test on a gray-scale image, one has to simply define region mean $\langle\mu\rangle$ and scatter or variance $\langle\sigma^2\rangle$ by:

$$\langle\mu\rangle = \frac{1}{N_R} \sum_{(r,c)\epsilon R} f(r,c)$$

&

$$\langle\sigma^2\rangle = \sum_{(r,c)\in R} (f(r,c) - \langle\mu\rangle)^2$$

where r and c are the row and column coordinates of the pixels whose coordinates belongs to the set of growing region R, f is image under segmentation and N_R is the current count of pixels in the growing region.

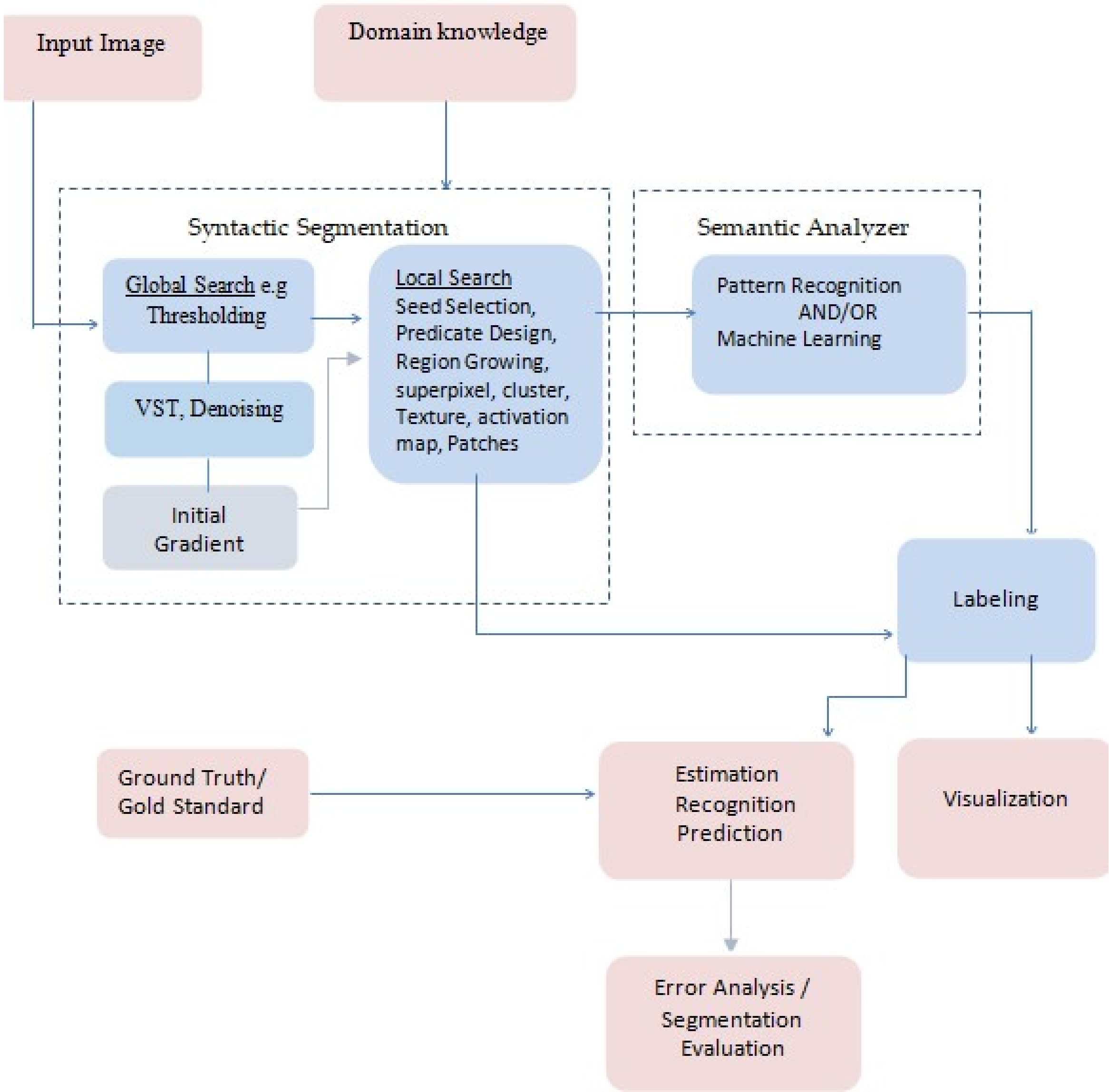


Figure 3. Proposed Schematic for Automation of SRG Segmentation

5. Novel Seed Selection Mechanism

The idea is to use multiple but scattered seeds to grow a distinct region rather than using connected set or 2x2 or 8x8 contiguous seeds. The seeds are chosen to lie on a regular polygon around the center of the image with a particular radius. This seed selection mechanism has a tendency to group pixels that belong to the same region, although the seeds are scattered all over the image as shown in Figure 4. This scheme is based on the observation that for various multi-modal images the polygonal seeds seems to have the same gray level and thus are homogenous. The size of the radius and number of vertices in a polygon is a domain specific problem. The method does not need to estimate density function as before though exploration exists in determining radius and center of the polygon. The advantage of this scheme over histogram based scheme is to segment with few seeds as compared to a large bank of seeds obtained via peak and valley analysis of histogram.

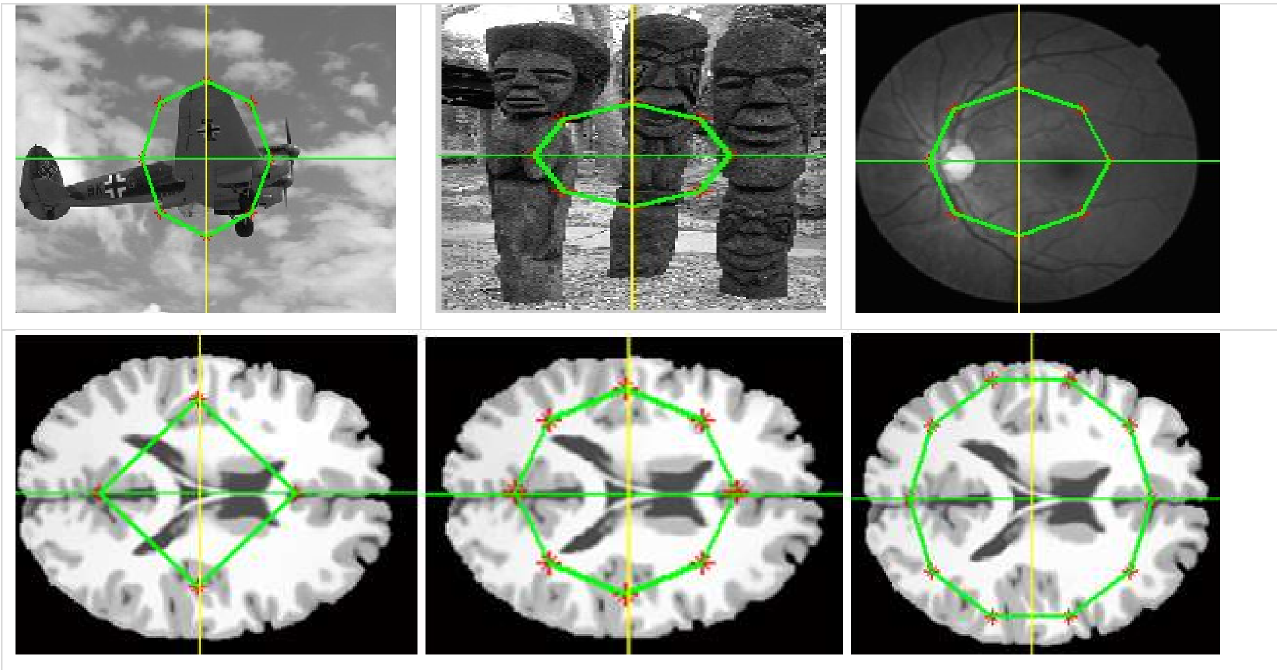


Figure 4. Novel and Proposed Polygonal Seed Selection Mechanism

We attempt to improve seeded region growing results using polygonal seed selection mechanism and employ K-Means algorithm at post-processing stage to merge the small noisy segments but medical images for e.g. brain MR slice is by nature a disconnected object especially the gray matter hence an ideal segmentation with the region growing is extremely difficult. The results before post-processing and after processing are shown in Figure. 5. We observed that the best segmentation is achieved only for the central axial slice (Row 1 of Figure. 5) so it still seems difficult that region growing can perform batch or volume processing without adding expert knowledge. For Watershed segmentation, Regional maxima are used to get foreground markers from brain MR images which belong to gray matter (GM) region or white matter (WM) in axial slices. The gradient magnitude is used as conventional segmentation function and its watershed transformation is unable to distinguish between CSF, GM, and WM pixels as shown in Figure 5 (Row 1). We make use of polygonal foreground markers and found improvement in segmentation results Figure 5 (Row 2). The control of foreground markers can be done using radius, center, and shape of a polygon. Our preliminary results of polygonal seeds with watershed are shown in Figure 6. Improved results are given in Figure 7.

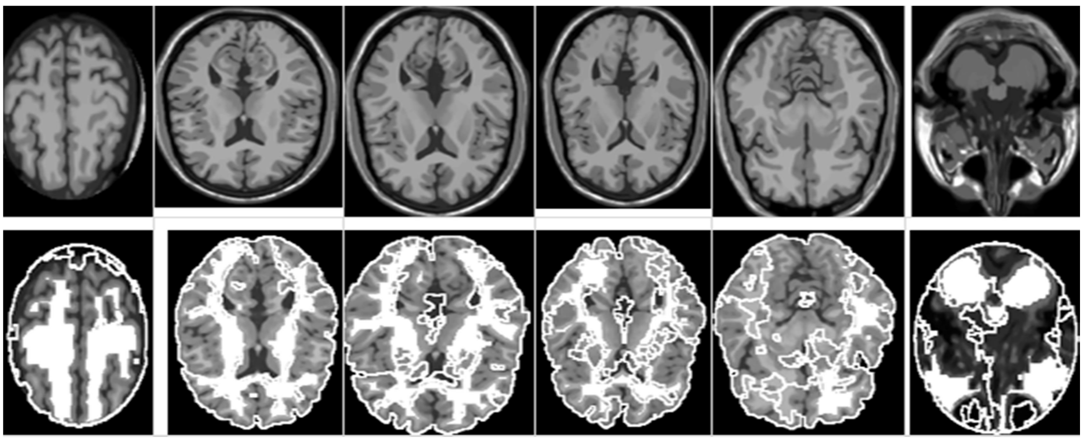


Figure 5. Watershed Foreground and Background Markers with out Polygonal Seed

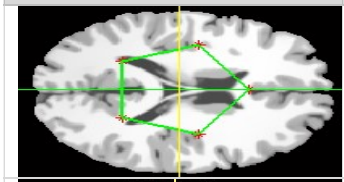
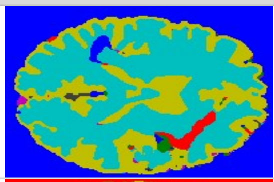
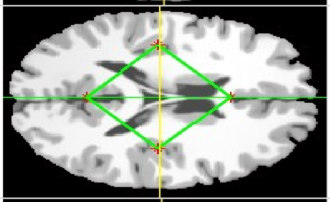
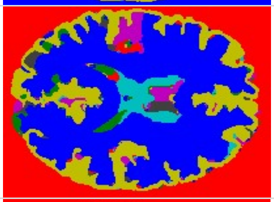
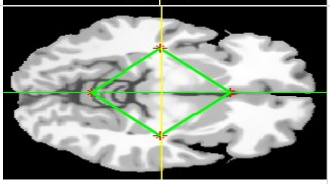
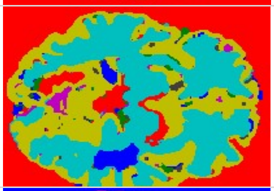
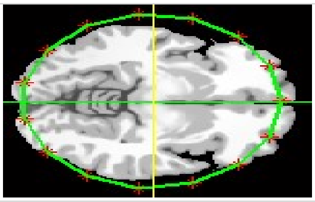
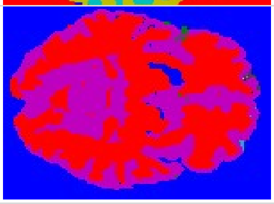
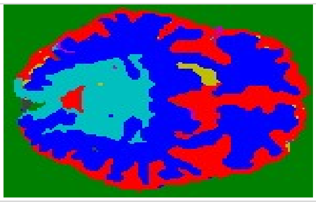
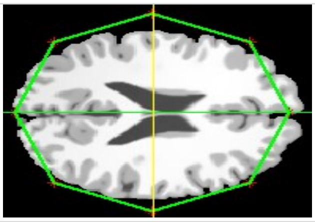
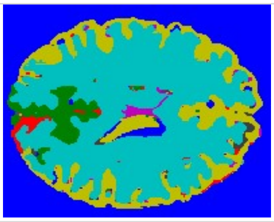
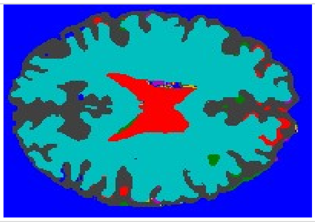
Input Seeds	Before Post Processing	Before Post Processing	K-means with 32 clusters
		numSegments = 155	
		numSegments = 412	
		numSegments = 481	
		numSegments = 204	
		numSegments = 204	

Figure 6. Improved region growing results with polygonal seeds

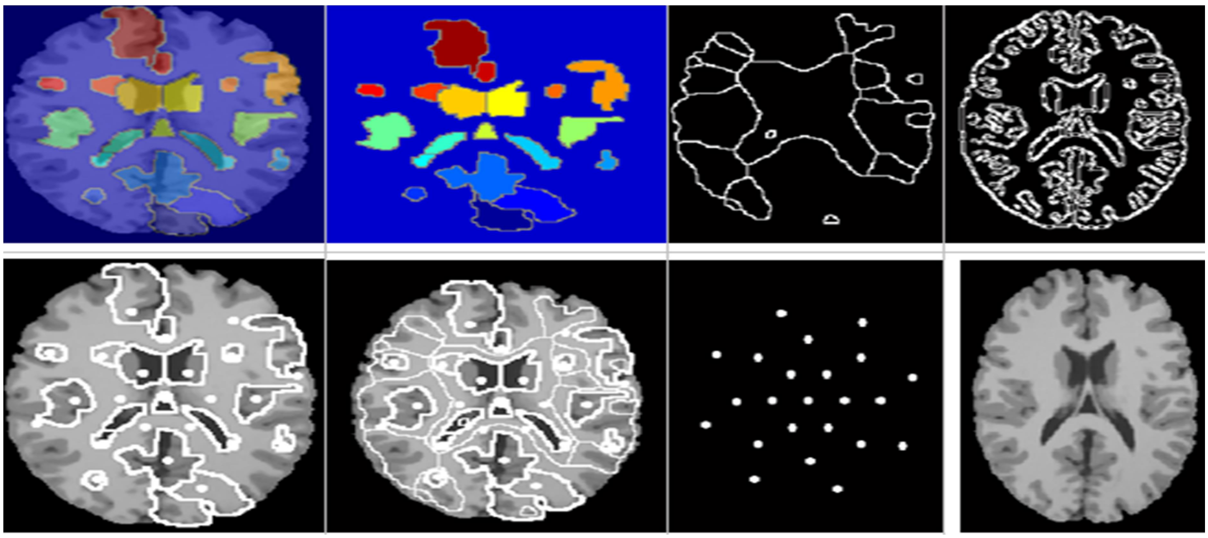


Figure 7. Preliminary Watershed results with Polygonal seeds markers

We also attempt to apply K-Means with K=10 on brain images without skull stripping to retrieve more cluster information and found improvement in initial conditions as shown in Figure 7.

Finally we compare improved K-Means results with other region-based segmentation. The result was presented in Figure 8. which shows that segmentation of the brain region is quite challenging. Figure 8, Row 1 shows otsu's segmentation results which seems quite satisfactory for only White matter segmentation. Figure 8, Row 2 shows region growing results which seems better than otsu but again needs Improvement. Watershed results in Figure 8, Row 3 are quite unsatisfactory and Finally, Figure 8, Row 4 presents K-Means clusters showing Improvement due to initial polygonal seed guidance.

6. Conclusion

Traditional K-Means cluster always segment background (BG) into various classes showing extreme misclassification. When K-Means is used with polygonal seed for initialization; improved clustering is observed with clear separation between various regions of the brain. Less improvement has been seen in Watershed segmentation with proposed polygonal seed. In the future, we aim for brain lesion detection and biological mapping of various brain regions by combining our proposed technique and framework with recent machine learning models and expert knowledge.

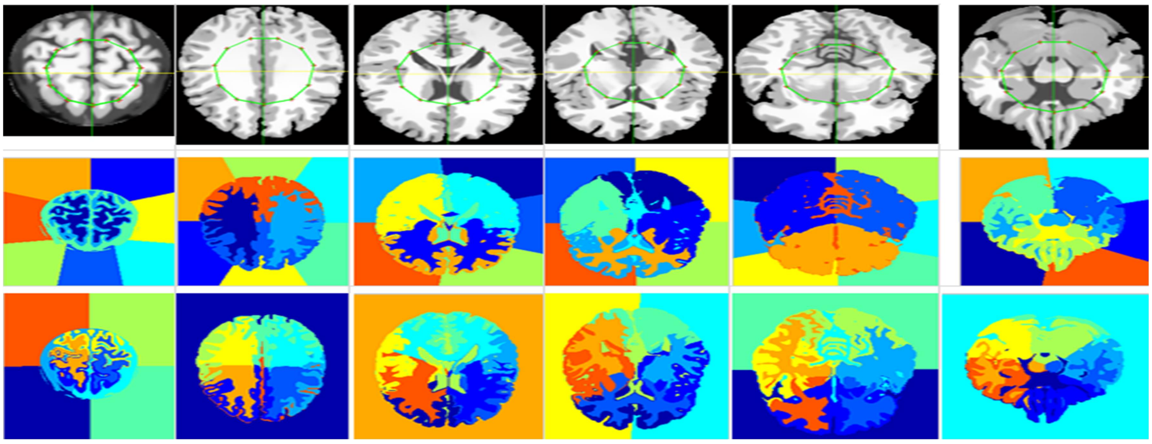


Figure 8. Row 1: Brain Slices; Row 2: K-Means with Random Seeds; Row3: K-Means with Polygonal Seeds

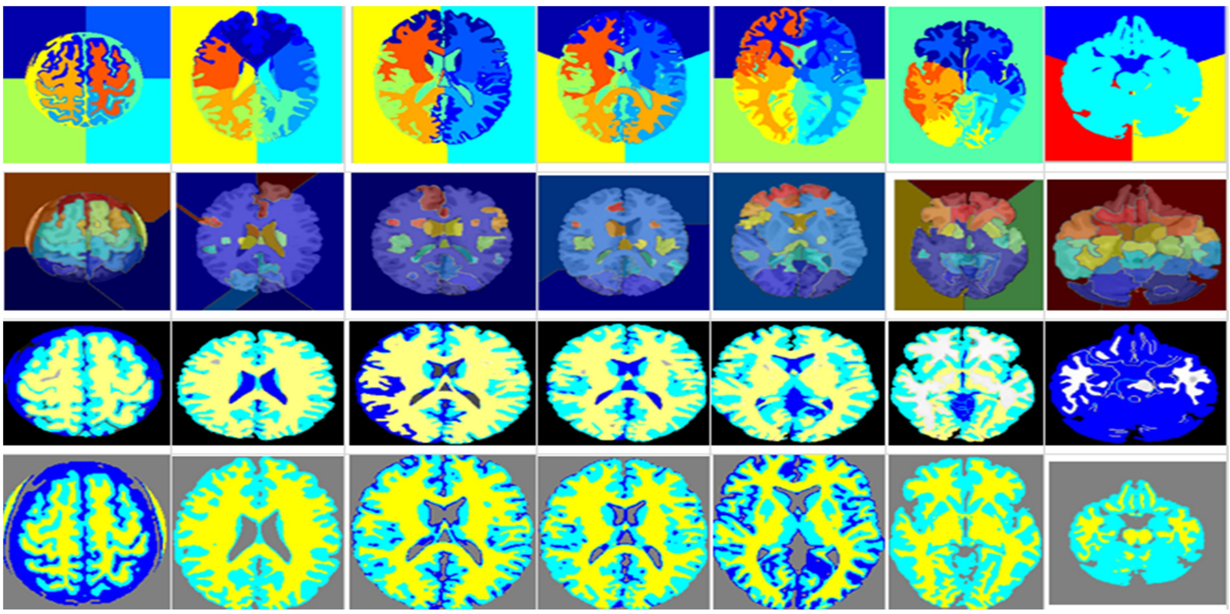


Figure 9, Row 1: Otsu; Row 2: Region Growing; Row 3: Watershed; Row 4: Improved K-Means

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