

## REGION GROWING SEGMENTATION OF MAGNETIC RESONANCE IMAGES USING METRIC TOPOLOGICAL $\epsilon$ - NEIGHBOURHOODS

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**Abstract:** Segmentation of medical images using seeded region growing method is one of the important techniques. Seeded region growing method based segmentation is very useful in the field of medicine for diagnosis and treatment of diseases. In this article, we propose a new seeded region growing segmentation algorithm based on metric topological  $\epsilon$  - neighbourhoods of different metrics and grouping criterion for segmentation of interested object from the magnetic resonance images. The quality of the segmented images is measured by the evaluation measure "Accuracy"

**Keywords:** Metrics, Region Growing, Segmentation, Topological Neighbourhoods.

**Introduction:** Image segmentation is an important task in medical image analysis. Medical image segmentation plays an important role in diagnosis of diseases for the radiologists. Image segmentation is a process of partitioning a digital image into disjoint regions of connected pixels that are homogeneous with respect to some characteristics such as gray level or colour. Image segmentation algorithms are mainly based on two properties, detecting discontinuities and similarities. The first category is based on the abrupt changes in intensity and the second category is based on grouping the set of similar pixels satisfying predefined criterion. Some of the image segmentation algorithms based on the above techniques are edge detection, thresholding, region growing, region splitting and merging, clustering, watershed algorithm etc.,

Geng - Cheng Lin et al., [1] proposed a novel fuzzy knowledge based seeded region growing for multispectral magnetic resonance images and proved that this method is more efficient than the K-means and support vector machine methods. Maria Kallergi et al., [7] developed local thresholding and region growing algorithms and applied to digitized mammograms and proved that computerized parenchymal classification of digitized mammograms is possible and independent of exposure. Pastore, J. et al., [9] described an automatic segmentation of computerized axial tomography images with tumors by means of alternating sequential filters of mathematical morphology and connected components extraction based on continuous topology concepts. Gnanambal Ilango and R. Marudhachalam [2] presented an automatic method relevant to medical image segmentation by means of fuzzy hybrid filters for denoising and topological concepts to extract connected components and edge detection. Junchai Gao et al., [5] proposed a threshold and edge detection fused segmentation algorithm which considers not only the adjacent uniformity but also the local contrast.

In this article, a new seeded region growing segmentation algorithm is proposed based on  $\epsilon$  - neighbourhoods of different metrics and grouping criterion.

**Seeded Region Growing Method Of Segmentation:** Region based segmentation is a classical method. This method tries to extract the object that is connected based on some predefined criterion. This criterion can be based

on the intensity information and edges in the image. One of the region based segmentation methods is the Seeded Region Growing method. This is a procedure that groups pixels in whole image into sub regions based on predefined criterion and processed in four steps. (i) Select a seed pixel in the original image. (ii) Select a set of similarity criterion such as gray level or colour and set up a stopping rule. (iii) Grow region by appending to the seed, those neighbouring pixels that have predefined properties similar to seed pixel. (iv) Stop region growing when no more pixels meet the criterion for inclusion in that region.

Here from the histogram of the image, the gray level of the region of interest is selected. Considering the gray level of the region of interest, a seed point is selected as a point having maximum number of  $\epsilon$  - neighbourhoods of different metrics. For the similarity criterion, a grouping criterion is defined based on metric and gray level difference. The connected region of interest is grown by including the  $\epsilon$  - neighbours of the seed point satisfying the grouping criterion with the seed point. The quality of the segmented tumor from the magnetic resonance images of brain affected by tumor by the proposed algorithm is compared with the ground truth images and the results are analyzed.

### Basic Definitions : Definition 3.1[8]

A metric on a set  $X$  is a function  $d: X \times X \rightarrow \mathbf{R}$  having the following properties:

- i.  $d(x, y) \geq 0 \quad \forall x, y \in X$ ; equality holds iff  $x = y$ .
- ii.  $d(x, y) = d(y, x) \quad \forall x, y \in X$ .
- iii.  $d(x, z) \leq d(x, y) + d(y, z) \quad \forall x, y, z \in X$ .

Given a metric  $d$  on  $X$ , the number  $d(x, y)$  is called as the distance between  $x$  and  $y$  in the metric  $d$ . For a given  $\epsilon > 0$ , consider the set

$B_d(x, \epsilon) = \{y: d(x, y) < \epsilon\} = B(x, \epsilon)$  of all points  $y$  whose distance from  $x$  is less than  $\epsilon$ . Here  $B_d(x, \epsilon)$  is called the  $\epsilon$  - ball centered at  $x$ . If  $d$  is a metric on the set  $X$ , then the collection of all  $\epsilon$  - balls  $B_d(x, \epsilon)$  for  $x \in X$  and  $\epsilon > 0$ , is a basis for a topology on  $X$ , called metric topology induced by  $d$ . A set  $U$  is open in the metric topology induced by  $d$  iff for

each  $y \in U$ , there is a  $\delta > 0$  such that  $B_d(y, \delta) \subset U$ . If  $X$  is a topological space,  $X$  is said to be metrizable if there exists a metric  $d$  on the set  $X$  that induces the topology of  $X$ . A metric space is a metrizable space  $X$  together with a specific metric  $d$  that gives the topology of  $X$ .

**Definition 3.2[4]:** An image may be defined as a two-dimensional function  $f(x, y)$ , where  $x$  and  $y$  are spatial (plane) coordinates, and the amplitude of  $f$  at any pair of co-ordinates  $(x, y)$  is called the intensity or gray level of the image at that point. If  $x, y$  and the intensity values of  $f$  are all finite, discrete quantities, we call the image a digital image. A digital image is composed of a finite number of elements  $(x, y)$  each of which has a particular location and value. These elements are called picture elements or pixels.

**Definition 3.3[3]**

Let  $S^2 = S \times S \subset N \times N$ , where

$$S^2 = \{(x, y); x = 1, 2, 3, \dots, m; y = 1, 2, 3, \dots, n\}$$

be the set of spatial co-ordinates of an image. For any metric space  $(S^2, d)$  any  $p \in S^2$  and any  $\varepsilon > 0$ , consider the set  $N_{d, \varepsilon}(p) = \{q; d(p, q) < \varepsilon + 1\}$ .  $N_{d, \varepsilon}(p)$  is called the (open)  $\varepsilon$  - neighbourhood of  $p$  in  $S^2$ .  $N_{d, \varepsilon}(p)$  is an open ball centered at  $p$ .

**Definition 3.4[6]**

Let  $p = (x_1, y_1), q = (x_2, y_2) \in S^2$ .

Consider the functions

i.  $d_4 : S \times S \rightarrow R$ , defined by

$$d_4(p, q) = |x_1 - x_2| + |y_1 - y_2|.$$

Then  $(S^2, d_4)$  is a metric space. The metric  $d_4$  is called the City - Block metric or Manhattan metric.

ii.  $d_8 : S \times S \rightarrow R$ , defined by

$$d_8(p, q) = \max\{|x_1 - x_2|, |y_1 - y_2|\}$$

Then  $(S^2, d_8)$  is a metric space. The metric  $d_8$  is called the Chessboard metric.

**Definition 3.5[3]**

For any point  $p$ , the 4 - neighbourhood of  $p$  denoted by  $N_{d_4, 1}(p)$  is defined as

$$N_{d_4, 1}(p) = \{q \in S^2; d_4(p, q) < 2\}.$$

$N_{d_4, 1}(p)$  is also denoted by  $N_4(p)$  and the 8 - neighbourhood of  $p$  denoted by  $N_{d_8, 1}(p)$  is defined as

$$N_{d_8, 1}(p) = \{q \in S^2; d_8(p, q) < 2\}.$$

$N_{d_8, 1}(p)$  is also denoted by  $N_8(p)$ .

**Definition 3.6[3]**

For any point  $p$ , the 4 - neighbours of  $p$  are  $N_{d_4, 1}(p) - \{p\}$  and the 8 - neighbours of  $p$

are  $N_{d_8, 1}(p) - \{p\}$ .

**Definition 3.7[3]**

Let  $M \subseteq S \times S$

where

$M = \{(x, y \pm k); \text{where } k = 0, 1, 2, 3 \dots\}$ . Let

$p = (x_1, y_1), q = (x_2, y_2) \in M$ . Consider the

function  $d_V : M \rightarrow R$  defined by

$$d_V(p, q) = |x_1 - x_2| + |y_1 - y_2|.$$

$(M, d_V)$  is a metric space. For any point  $p$ , the  $V_\varepsilon$  neighbourhood of  $p$  is defined as

$$N_{d_V, \varepsilon}(p) = \{q; d_V(p, q) < \varepsilon + 1\}.$$

Hence the  $V_1$  neighbourhood of  $p$  is

$$N_{d_V, 1}(p) = \{q; d_V(p, q) < 2\}$$

and the  $V_2$  neighbourhood of  $p$  is

$$N_{d_V, 2}(p) = \{q; d_V(p, q) < 3\}.$$

The  $V_1$  neighbours of  $p$  are  $N_{d_V, 1}(p) - \{p\}$  and the  $V_2$

neighbours of  $p$  are  $N_{d_V, 2}(p) - \{p\}$ .

**Definition 3.8[3]**

Let  $M \subseteq S \times S$

where

$$M = \{(x + k, y + k)\} \cup \{(x - k, y - k)\}; \text{where } k = 0, 1, 2, 3 \dots\}$$

Let  $p = (x_1, y_1), q = (x_2, y_2) \in M$ .

Consider the function  $d_{RT} : M \rightarrow R$  defined by

$$d_{RT}(p, q) = \frac{1}{2} [|x_1 - x_2| + |y_1 - y_2|]$$

$(M, d_{RT})$  is a metric space. For any point  $p$ , the

$RT_\varepsilon$  neighbourhood of  $p$  is defined as

$$N_{d_{RT}, \varepsilon}(p) = \{q; d_{RT}(p, q) < \varepsilon + 1\}.$$

Hence the  $RT_1$  neighbourhood of  $p$  is defined as

$$N_{d_{RT}, 1}(p) = \{q; d_{RT}(p, q) < 2\}$$

and the  $RT_2$  neighbourhood of  $p$  is defined as

$$N_{d_{RT}, 2}(p) = \{q; d_{RT}(p, q) < 3\}.$$

$N_{d_{RT}, 1}(p)$  is also denoted by  $R_3(p)$ . The  $RT_1$

neighbours of  $p$  are  $N_{d_{RT}, 1}(p) - \{p\}$  and the  $RT_2$

neighbours of  $p$  are  $N_{d_{RT}, 2}(p) - \{p\}$ .

**Definition 3.9[3]**

Let  $M \subseteq S \times S$

where

$$M = \{(x - k, y + k)\} \cup \{(x + k, y - k)\}; \text{where } k = 0, 1, 2, 3 \dots\}$$

Let  $p = (x_1, y_1), q = (x_2, y_2) \in M$ .

Consider the function  $d_{LT} : M \rightarrow R$  defined by

$$d_{LT}(p, q) = \frac{1}{2} [|x_1 - x_2| + |y_1 - y_2|]$$

$(M, d_{LT})$  is a metric space. For any point  $p$ , the

$LT_\varepsilon$  neighbourhood of  $p$  is defined as

$N_{d_{LT,\varepsilon}}(p) = \{q; d_{LT}(p, q) < \varepsilon + 1\}$ . Hence the  $LT_1$  neighbourhood of  $p$  is defined as  $N_{d_{LT,1}}(p) = \{q; d_{LT}(p, q) < 2\}$  and the  $LT_2$  neighbourhood of  $p$  is defined as  $N_{d_{LT,2}}(p) = \{q; d_{LT}(p, q) < 3\}$ .  $N_{d_{LT,1}}(p)$  is also denoted by  $L_3(p)$ . The  $LT_1$  neighbours of  $p$  are  $N_{d_{LT,1}}(p) - \{p\}$  and the  $LT_2$  neighbours of  $p$  are  $N_{d_{LT,2}}(p) - \{p\}$ .

**Definition 3.10**

**Grouping criterion:** Let  $X$  be an image in levels of gray and  $\mathfrak{S}$  a topology associated with  $X$  and let  $Y \subset \mathfrak{S}$ . Let 'd' be a metric on  $X$ . Define  $\varphi : Y \times X \rightarrow R$  such that  $\varphi((A, x)) = m$  where  $m$  is the maximum of the gray level difference between  $x$  and the elements of  $A$ . Let  $A \in Y$ . Given a fixed  $\varepsilon$  and  $\delta$ , an element  $x \in X$  is said to belong to  $A$  if  $d(x, y) < \varepsilon + 1$  for some  $y \in A$  and  $\varphi((A, x)) < \delta$ .

**Proposed Segmentation Algorithm:**

**VLTRT Algorithm:** Let  $X$  be an image in levels of gray.

**Step I:** From the histogram of the image, select the gray level of the region of interest to be segmented.

**Step II:** Find the seed point of the region of interest. Here the seed point is a point with maximum number of vertical neighbours with gray level difference less than  $\delta$  which is very small. If more than one point has the maximum number of vertical neighbours then choose any one of those points as the seed point.

Let  $A_1 = \{x\}$  where  $x$  is the seed point of the region of interest.

**Step III:** Choose  $\varepsilon = 1$  and  $\delta = 2$ . If  $\exists$  a point  $y \in X$  where  $y \notin A_1$  such that  $d_V(x, y) < \varepsilon + 1$  and  $\varphi((A_1, y)) < \delta$  -----(1) then include  $y$  in  $A_1$  and rename it as  $A_2$ .

Repeat Step III again and again for the elements of  $A_2$  till  $\exists$  no point  $y \in X$  satisfying the condition (1). That is all the vertical neighbours of  $A_1$  are obtained.

**Step IV:** If  $\exists$  a point  $y \in X$  where  $y \notin A_2$  such that  $d_{LT}(z, y) < \varepsilon + 1$  where  $z \in A_2$  and  $\varphi((A_2, y)) < \delta$  -----(2) then include  $y$  in  $A_2$  and rename it as  $A_3$ .

Repeat Step IV again and again for the elements of  $A_3$  till  $\exists$  no point  $y \in X$  satisfying the condition (2). That is all the LT neighbours of  $A_2$  are obtained.

**Step V:** If  $\exists$  a point  $y \in X$  where  $y \notin A_3$  such that  $d_{RT}(z, y) < \varepsilon + 1$  where  $z \in A_3$  and  $\varphi((A_3, y)) < \delta$  -----(3) then include  $y$  in  $A_3$  and rename it as  $A_4$ .

Repeat Step V again and again for the elements of  $A_4$  till  $\exists$  no point  $y \in X$  satisfying the condition (3). That is all the RT neighbours of  $A_3$  are obtained.

The set  $A_4$  is the segmented region of interest.

**Evaluation Measure:** Let  $X$  be the set of pixels in the image. Define the ground truth  $T \subset X$  as the set of pixels that were labeled as tumor by the expert. Similarly define the segmented tumor  $S \subset X$  as the set of pixels that were labeled as tumor by the algorithm.  $\bar{T}$  and  $\bar{S}$  are the set of pixels that were labeled as non-tumor by the experts and algorithm respectively. The true positive (TP) set is defined as  $TP = T \cap S$ , i.e., the set of pixels that were labeled as tumor by the expert and the algorithm. The true negative (TN) set is defined as  $TN = \bar{T} \cap \bar{S}$ , i.e., the set of pixels that were labeled as non-tumor by the expert and the algorithm. The false negative (FN) set is defined as  $FN = T \cap \bar{S}$ , i.e., the set of pixels that were labeled as tumor by the expert and non-tumor by the algorithm. The false positive (FP) set is defined as  $FP = \bar{T} \cap S$ , i.e., the set of pixels that were labeled as non-tumor by the expert and tumor by the algorithm.

The segmentation evaluation measure "Accuracy" is defined as

$$\text{Accuracy} = \frac{n(TP) + n(TN)}{n(TP) + n(TN) + n(FP) + n(FN)}$$

**Experimental Work, Result Analysis And Discussion:**

In this work, magnetic resonance images of brain affected by tumor are taken. The seed point of the region of interest is selected using the histogram of the image and the metric topological  $\varepsilon$ -neighbourhoods. The region of interest is grown from the seed point using the metric topological

$\varepsilon$ -neighbourhoods  $N_{d_V,\varepsilon}(p)$ ,  $N_{d_{LT,\varepsilon}}(p)$ ,  $N_{d_{RT,\varepsilon}}(p)$

and the grouping criterion. The proposed region growing segmentation algorithm is implemented using MATLAB 7.0. The performance of the proposed algorithm is evaluated using the segmentation evaluation measure 'Accuracy'. Table 1 shows the accuracy and quality of segmentation values. Fig 1 shows the ground truth images. Fig 2 shows the original magnetic resonance images of brain affected by tumor, the corresponding segmented region and the segmented region with boundary using the proposed VLTRT algorithm.

**Conclusion :** In this work, a new region growing segmentation algorithm based on metric topological  $\varepsilon$ -neighbourhoods and grouping criterion is introduced. To demonstrate the performance of the proposed region growing segmentation algorithm, experiments have been conducted on magnetic resonance images of brain affected by tumor. The performance of the proposed segmentation algorithm is measured using the segmentation evaluation measure 'Accuracy'. The experimental results indicate that the quality of segmentation by the proposed VRTL algorithm is

98.52% or more. This is a new approach for region growing segmentation which is based on metric topological  $\mathcal{E}$ -neighbourhoods.

**Figures:**

EVALUATION MEASURE	IMAGE 1	IMAGE 2	IMAGE 3	IMAGE 4
ACCURACY	0.9852	0.9888	0.992	0.991
QUALITY OF SEGMENTATION	98.52%	98.88%	99.20%	99.10%

Table 1 - Accuracy and Quality

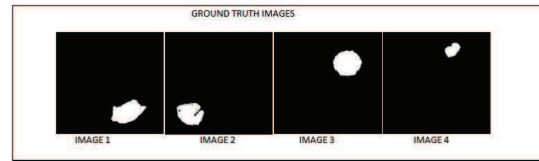


Fig 1 – Ground Truth Images

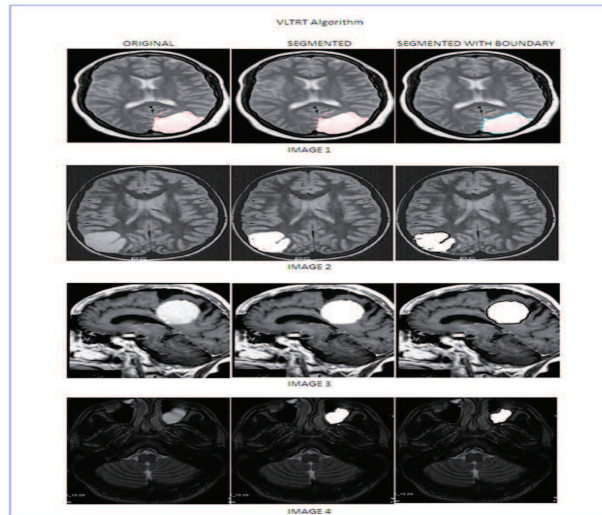


Fig 2 – Segmentation by VLTRT Algorithm

**Acknowledgment:** The authors thank The University Grants Commission, India, to carry out this research work.

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