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An Automated Brain MRI image segmentation using Generic Algorithm and TLBO

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ABSTRACT

In this paper, automated brain MRI image segmentation based on Teaching-learning based optimization. The proposed method is the combination of TLBO and a generic algorithm based segmentation method, which is named variable string length genetic segmentationstrategy (VGAPS) which is capable of evolving the number of segments present in the image automatically. The allotment of pixels to the segment is based on Line symmetry based methods which is much efficient and effective than Line symmetry and Euclidean distance based methods. The cluster enters were deployed inside the chromosome whose value changes in each iteration based on the fitness calculated through the TLBO. The result demonstrates that the proposed technique is well suited for medical image segmentation with satisfactory result.

Keywords: genetic algorithm, line symmetry method, TLBO.

1. INTRODUCTION

Image segmentation is a process in which the image is divided into multiple clusters by depending upon a different pixel attributes like intensity, tint, tone, aspect ratio etc.; into consideration. The purpose for image segmentation is to simplify the image representation to more meaningful, significant way to analyze. The success of the image analysis is mainly depending on the standard of segmentation. In the field of computer assist recognition of tumors in medical images, Segmentation plays aessential role and often claims to be one of the preliminary preprocessing task for medical image analysis and it is a challenging task because of intrinsically imprecise nature of images.

Segmentation is one of the crucial phase for identification of any abnormalities in the brain tissues.

By performing the segmentation of MRI image, it makes easier to analyze different components of brain like white matter, grey matter and brain fluids. It makes the task of the radiographer ease by quantizing the white and grey matter to identify neurodegenerative disorders. But we come across the challenges like poisson noise.

Many segmentation algorithms are there to perform segmentation, where clustering is one of the unsupervised techniques to perform segmentation in effective and economic way. There were many segmentation techniques like K-mean[2], Fuzzy K-mean[3], are used for segmenting medical images. In this paper, a unique automated segmentation technique based on line symmetry based approach is used. TLBO algorithm is beening used along with the line symmetry based approach to calculate the fitness function of clusters. Fuzziness is used to calculate the both convex and non-convex clusters. Fuzziness is used to calculate the membership value of the pixel with every segment to assign it to the appropriate segment and assigns the value from the segment.

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The paper is arranged as section-II Image preprocessing to eliminate the poisson noise using harmonic mean, section-III presents about the genetic algorithm based variable string length based segmentation, Section-IV presents the qualitative results of the suggested technique and the lastly. Section-V presents the analysis and conclusion of the MRI brain image segmentation.

2. IMAGE PREPROCESSING TO ELIMINATE POISSON NOISE BY USING THE TECHNIQUE OF HARMONIC MEAN

While the MRI image is being acquired when the device is not calibrated in an appropriate way the image might end up with ill association with measurement of the luminance which leads to inappropriate quantization of light and photon detection if any such image is segmented without preprocessing it may lead to misinterpretation. So the image has to be preprocessed prior to segmentation of image.

Images with poisson noise will have temporal and spatical randomness because of extreme light conditions or poor light conditions during capturing the images at multiple dimensions. Poisson noise obeys the poison distribution.The square root of intensity of the image is directly proportional to root average value of noise.

By using the technique of harmonic mean it computes the mean among the surrounded pixel intensities and updates the current pixel value.The harmonic mean for eight neighboring pixels will be given by

$$H_8 = \frac{8}{\sum_{n=1}^{8} \frac{1}{I_n}}$$

Where I is the intensity value of a neighbor. If, it consider 8 neighbors the numerator and the intensities will be eight else the numerator will be the number of neighbor that are considered for the up gradation.

3. GENETIC ALGORITHM BASED VARIABLE STRING LENGTH BASED SEGMENTATION

In this paper we automatically evaluate the clusters by making use of genetic algorithm. A variable string length based approach is used for segmenting the image.In this method, Aline symmetry based approach is used for deciding the belongingness to the segment using an index. So, The index value is optimized in each iteration to reach the global best solution. As it is a variable string length technique it can hold a variable number of clusters, i.e.; the *K* value which tells the number of clusters. Here, The Line symmetry based techniques could be applied to the cluster of any shape and size, until the cluster processes the same properties.

line symmetry based distance $d_{ps}(z, c)$with symmetric line be Z corresponding center be C is given by 2xC–Z.Let this be denoted by Z*.Let the K_{near} neighbors of Z* be at a Euclidean distance of $d_{es} = 1, 2, 3, 4\ldots..K_{near}$. then

$$d_{ps}(z,c) = d_{sym}(z,c)\, x d_{ed}(z,c)$$

$$d_{ps}(z,c) = \frac{\sum_{i=1}^{k_{near}} d_i}{knear} \times d_{ed}(z,c)$$

Where $d_{ed}(z, c)$ is the Euclidean distance from the line Z to the center C. And d_{sym} represents the line symmetric measure. Here from the equation it is clear that the value of *i*lies between 1 and the best K_{near} value. So the k_{near} value which we are going to choose must be optimal. If we assume it as 1, there will be no much impact on Euclidean distance and if incase the value of upper bound is too high then it may lead to un deterministic state. So the upper bound is taken close to 2.It must be considered that the K_{near} value is mostly depend on the distribution of the population. Now let us going in detail how this GA based automated segmentation algorithm works

3.1. Population Initialization

Population initialization is the preliminary stage in the proposed technique. Here the chromosome were filled up with the real numbers that represents the coordinates(x & y) of the center of the cluster. If a chromosome *ch* represents the centers of the clusters k_{ch} in*d*dimensional space with length l_{ch} will be$d$xk_{ch}.

$$k_{ch} = (\text{rand}(\ ) \bmod (k_{max}-1))+2.$$

Where K_{max} is the upper bound of segments and the *rand()* function will generate a random number. So the number of cluster count lies between 2 and the max value.

3.2. Fitness Computation

Fitness is the next phase of the automated segmentationalgorithm, here we compute the fitness to compute the belongingness.

Here in this paper *Teacher Learner based Optimization (TLBO)* is used for achieving the better outcome. TLBO is a natural inspired population based technique always proceeds to the global solution. In TLBO, theinitial population is considered to be the group of learners and consist of multiple design variables which are analogues to different subjects offered to the learner. And the teacher is considered to be the best optimal solution obtained so far in the current iteration.In the Teacher's phase, learning from the teacher and inthe learning's phase learning through interacting through the learners.

Assignment of Lines: Every line Z_i where $1 \le Z_i \le n$ is assigned to the cluster K if $d_{ps}(z_i, c_k) \le d_{ps}(z_i, c_j)$ where j = 1, 2, 3……k and k ≠ j and $d_{sym}(z_i, c_k) \le \theta$, where θ is the threshold. For $d_{sym}(z_i,c_k)> \theta$, line z_i is assigned to some cluster L when $d_{ed}(zi, c_L) \le d_{ed}(zi, cj)$, j = 1, 2, 3, …. k.j≠L. It can be simple understood as the line Z_i will be assigned to the cluster whose P_S distance is minimum and provided its value must be below the threshold (θ). Otherwise, sometimes the Euclidean distance is also considered to assign the line to the cluster, Even Euclidean distance is also considered because sometimes when the cluster center are not yet evaluated then the minimum d_{ps}value for a line is expected to be larger.Using the Euclidean distance in such cases is appears to be more suitable. So, for setting the value of θ(threshold) where we take the d_{ps} into consideration. In case, if a line is symmetric with some cluster center then obviously the symmetric distance computed will be very minimal and it would be bounded as follows.

Let the d_{max} be the maximum of the nearest neighbor distance available in the cluster set i.e $d_{nn}^{\max}$ = $\max_i$ = 1, 2, 3, ……n.$d_{nn}(x_i)$, where $d_{nn}(x_i)$ is the closest neighborhood distance of x_i. Incase of any uncertainties like

$$\frac{d_1 + d_2}{2} \le d_{nn}^{\max}$$

Where

$$d_1 \le \frac{d_{nn}^{\max}}{2}$$

$$d_2 \le \frac{3Xd_{nn}^{\max}}{2}$$

Here d_1 and d_2 bound the sphere of radius $d_{nn}^{\max}$. Generally the threshold value i.e θ is set to $d_{nn}^{\max}$ which performs automated segmentation. In every iteration the cluster centroid is updated by calculating the mean.

3.2.1. Fitness Calculation

In every iteration the flintiness value *sym-index* is calculated and set to optimal for performing better segmentation.Every time the fitness is computed for the population and the element having the highest *sym* is considered to be the teacher for the next phase.

3.3. Teacher Learner Based Optimization

Following is the optimization technique for identifying and optimizing clusters,which involves two phases one is teaching phase and learning phase.

3.3.1. Initialization

Below are the notations we use in TLBO,

N: Represents number of learners in the class

CO: Represents courses offered.

MI: Represents the maximum number of iterations.

Let P will be the randomly initialized initial population in the search space which is bounded by the matrix of rows N representing the learners and Columns CO representing the courses offered. The j^{th} parameter of the i^{th} learner is given by

$$P_{(i,j)}^{0} = P_{j}^{\min} + const * \left(P_{j}^{\max} - P_{j}^{\min} \right)$$

where

$P_j^{\max}$ and $P_j^{\min}$ represents the max and min values of the j^{th} parameter and *const* is the random value within the range (0, 1). The parameter of the i^{th} learner for the current generation G is given by

$$P_i^G = \left(P_{(i,1)}^G, P_{(i,2)}^G, P_{(i,3)}^G \ldots \ldots P_{(i,j)}^G \ldots \ldots P_{(i,CO)}^G \right)$$

3.3.2. Teacher Phase

In the teacher phase of the TLBO the average of in subject for all the learners in the class at generation G is consider to be the mean parameteri.e$M^G$is given as

$$M^G = M_1^G, M_2^G, M_3^G \ldots \ldots M_J^G \ldots \ldots M_{CO}^G$$

Always the learners with the min P_i^G is considered to be the teacher for the corresponding iteration and every iteration they compute the latest P_i^G value and making the learner to teacher. Every time to obtain the improved set of learner it computes the random weighted vector from mean at the corresponding iteration and the desired mean value by adding the existing learners population.

$$Pnew_{(i)}^G = P_i^G + \ rand \ X \left(P_{Teacher}^G - T_F M^G \right)$$

Teaching Factor T_F generally set either 1 or 2 that decides the degree of change that has to be made to mean value.Anyway, it is not passed as the input parameter for the algorithm.The value of T_F could be randomly computed from

$$Tf = round\,(1 + rand\,(0, 1))$$

The latest value $Pnew_{(i)}^{G}$ is found to be better than the previous value P_i^G in the generation G. Then the value in previous iteration is replaced by the latest value $Pnew_{(i)}^{G}$.

3.3.3. Learner Phase

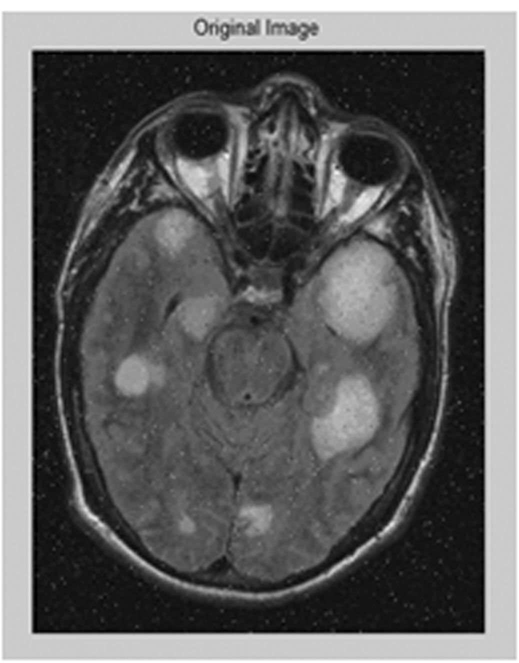
In this phase the learner will learn from the teacher as well as from the co-learners by random interaction with them increases their knowledge. Let us assume for a learner P_i^G and another learner P_j^G who is picked randomly such that i ≠ j. The i^{th} parameter from the matrix P_{new} is given as

$$Pnew_{(i)}^{G} = \begin{matrix} P_i^G + rand\ X\left(P_i^G - P_j^G\right) if\ f\left(P_i^G\right) > f\left(P_j^G\right) \\ P_i^G + rand\ X\left(P_j^G - P_i^G\right) otherwise \end{matrix}$$

4. RESULTS

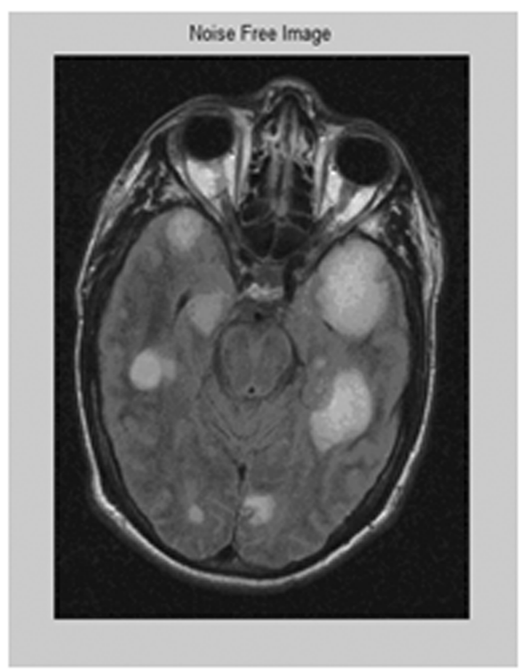
The performance of the suggested algorithm is experimented on a 512 × 512 brain MRI image which is corrupted with a impulse noise over the dynamic range [0-255], And the noise levels were varied from 10% to 90% to analyze the performance.

In our algorithm immediately after the image in preprocessed to remove the poisson noise, the image is segmented and then TLBO is been used to evaluate the segmentation, and then the color map is been applied in order to identify the hemorrhages in the brain, where a particular grey level is being highlighted



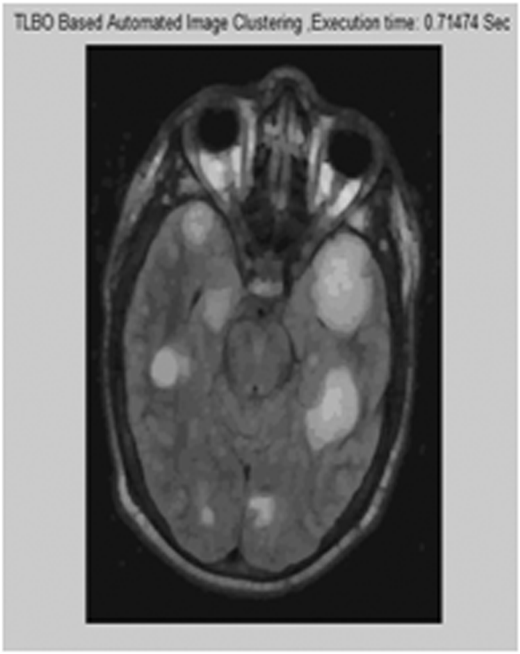
(a)

Figure (a): is the original T1 weighted image with poisson noise. second image



(b)

Figure (b): represents the noise free image(T1).



(c)

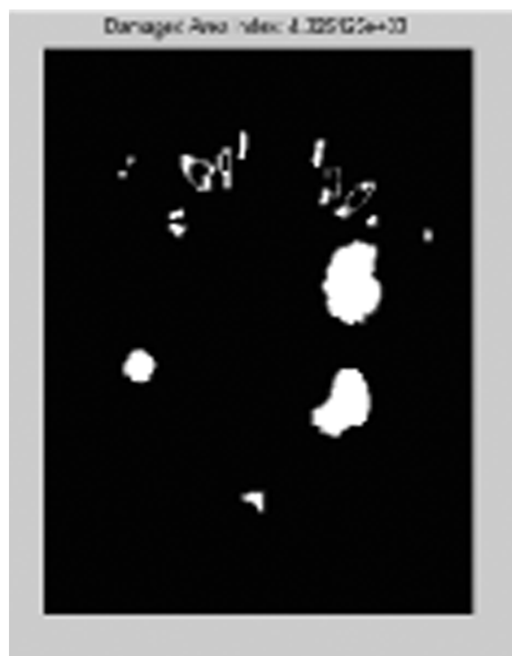
Figure (c): is the segmented image after preprocessing and elapsed time is 0.71474

(d)

Figure (d): is the color mapped image which identifies the pixel values with high intensities(grey parties in brain).

(e)

Figure (e): which highlights the white matter with grayscale value 170-190,but these are ordinary white matters,



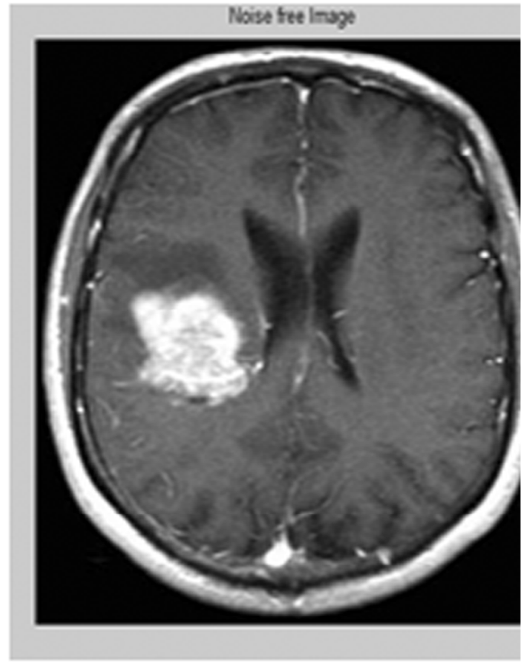
(f)

Figure (f): which highlights the suspected hemorrhages ,it highlights the parts with extreme white in T1 weighted image assumed to be the injury.

which indicated an injury. This may not give accurate results all the time in highlighting injuries but 85% of the time it could identify 98% of injuries. Here in below image the first image represents the original image with noise and the second one is the denoisedimage, third image represents the segmented image with execution time and the rest of the two images represents the color mapping of MRI images highlighting the abnormalities in the tissues with estimated approximate damage index of the area.

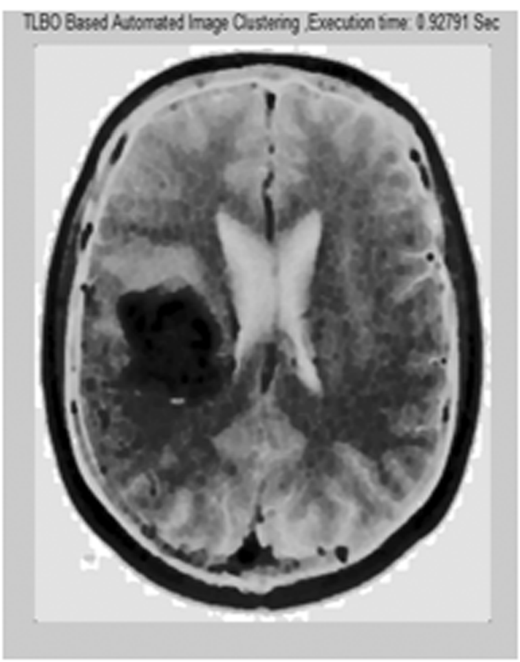
(g)

Figure (g): is the original T2 weighted image with poissonnoise and the second image



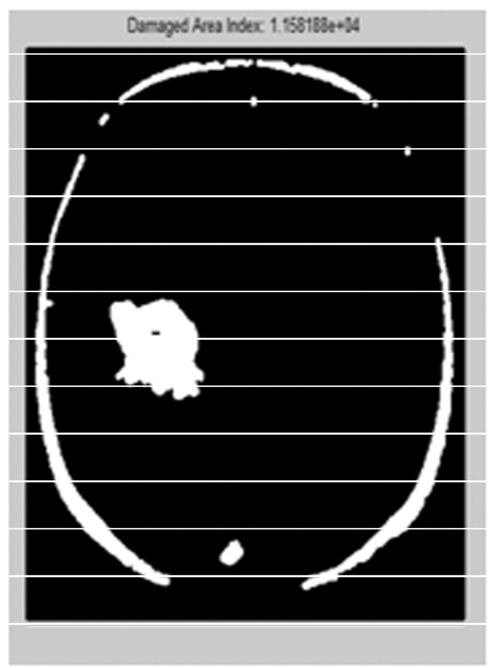
(h)

Figure (h): represents the noise free T2 weighted image after the harmonic mean.



(i)

Figure (i): which highlights the injury in the brain by segmentation, the dark part in the left portion represents the injury.



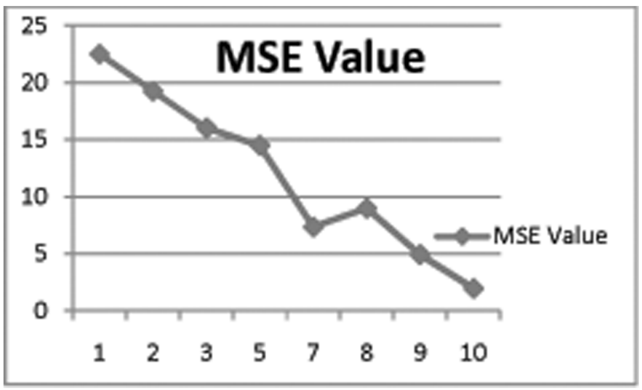
(j)

Figure (j): highlights the injury using the colormap for a T2 weighted image.

Here the noise free image is been compared and the original image using PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error), RMSE (Root Mean Square Error) and IQI (Image Quality Index) over the noise variance (σ) ranging from 0 to 10. MSE/RMSE values reduces with the reduce in noise variance.Table 1 below represents the computed value and fig I, J represents the plotted graph for the obtained results.

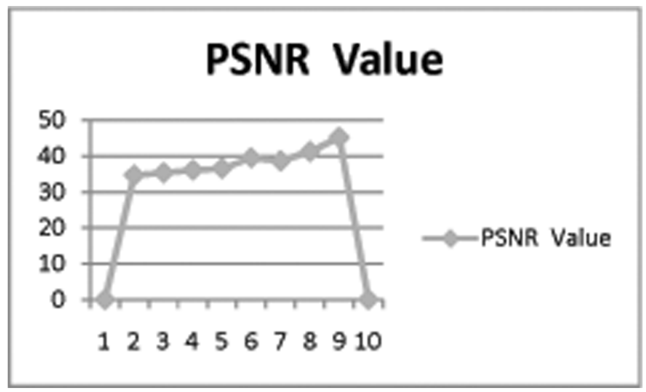
Table 1

S. No	*Noise Variance*	*PSNR Value*	*MSEValue*	*RMSEValue*	*IQIValue*
1	10	34.64	22.49	4.74	.97
2	9	35.32	19.24	4.38	.97
3	8	36.11	16.03	4.00	.98
4	7	36.55	14.49	3.80	.98
5	5	39.49	7.36	2.71	.99
6	3	38.62	8.98	2.99	.98
7	2	41.23	4.93	2.22	.99
8	1	45.18	1.98	1.40	.99



(k)

Figure (k): represents the graph associated with the RMSE and MSE of the image in Y axis and noise variance in X-axis, where MSE & RMSE ARE directly proportional to each other.



(l)

Figure (l): represents the PSNR (Peak Signal to Noise Ratio) of the image prior and after the normalization of noisewhich appears to be low at maximum noise variance.

5. ANALYSIS AND CONCLUSION

In this paper, it is show how to automatically segmenting the image using line symmetry technique along with Teacher Lerner based optimization to dynamically decide the number of segments and identifying the tumors in the brain by pixel intensity. The results obtained were effective . And we could easily de-noise the image and perform the segmention that the result obtained will be more accurate.

In our further work the image has to be enhanced so that every minute region in the brain could be segmented easily. More over in the proposed technique requires very minimal time for segmentation and the degree of belongingness of the pixel to a segment in the image.

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