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USER INTERACTIVE MULTI-VARIANT FEATURE GRAPH BASED ENERGY ESTIMATION TECHNIQUE FOR IMAGE SEGMENTATION

[1]S. SASIKANTH, [2]Dr. S. SURESH KUMAR

Research Scholar, Anna University, Chennai
[1]Assistant Professor, Department of Electronics and Communication Engineering,
[2]Vivekanandha College of Technology for Women
Tamil Nadu, India
[2]Principal, Vivekanandha College of Technology for Women
Tamil Nadu, India
E-mail: sasikanthphd@gmail.com

ABSTRACT

Image segmentation techniques are discussed earlier which uses color, intensity, pixel values and etc, and suffers with the problem of overlapping and grouping efficiency. We propose a novel method for image segmentation, using multi variant feature based energy estimation technique and works with interactive mode. Unlike other methods, the proposed methodology computes the feature energy of each pixel. The Feature energy represents the propagation of feature from one pixel to another and energy transition occurred at each of the neighbor pixel. The energy estimation is performed using various features of each pixel and its neighbors. An each pixel becomes the member of a group only if it carries same set of energy level or same set of features with possible little changes and comes within the energy threshold. The features used to compute the energy level are pixel values like red, green, blue and the number of neighbors and their values. The computed value is used to perform segmentation process, and produces higher rate of segmentation. The process will be performed iteratively still the user gets satisfied and provides new energy threshold value.

Key Terms: *Image Segmentation, Multi-Variant Features, Energy.*

1. INTRODUCTION

Digital image processing become more essential service for various domains like medical, identity management and etc.. There exists different approaches available and discussed earlier in literature for image segmentation, but each of them have some deviation in grouping similar pixel , i.e. it generates pixel overlapping and wrong classification. This generates poor results in both medical image processing and in domestic applications where the identity could be maintained.

Image segmentation is an essential process for most image analysis subsequent tasks. In particular, many of the existing techniques for image description and recognition depend highly on the segmentation results. Segmentation divides the image into its constituent regions or objects. Segmentation of medical images in 2D, slice by slice has many useful applications for the medical professional such as: visualization and volume estimation of objects of interest, detection of abnormalities, tissue quantification and classification, and more. The goal of segmentation is to simplify and/or change the representation of the image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (edge detection).

All pixels in a given region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). Segmentation algorithms are based on one of two basic properties of intensity values:

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discontinuity and similarity. The first category is to partition the image based on abrupt changes in intensity, such as edges in an image. The second category is based on partitioning the image into regions that are similar according to a predefined criterion. Histogram thresholding approach falls under this category.

There is various segmentation methods available like Genetic algorithm, which groups pixels according to the fitness function used. Also popular K-Means algorithm computes distance between pixel values to segment the image. The problem here is, both the solutions use a single feature value to compute the distance and fitness value. This makes the features or a pixel grouped under common category and produces less segmentation quality. This is where multi variant features are used, in which we use multiple feature values.

Multi-Variant Feature are variable image features like intensity, color values, ferat features, shape features and etc.. The segmentation quality highly depends on the feature selected for segmentation process. While segmenting image using color values and intensity measures, they converted to gray scale and similar intensity pixels are grouped and produces overlapped segmentation in selecting intensity value for the group. The genetic algorithms and K-means clustering methods uses only a single feature for segmentation process, also suffers with overlapping problem. This has to be overcome and a new strategic approach has to be designed which uses multiple features of the image for segmentation.

The image segmentation depends on variety of feature where the classification accuracy sit on the type of feature we used. The features of the image are extracted to compute some value which is called feature vector to represent the image in huge space. The classification is performed by computing any form of relevancy with set of feature vectors in the literature. There are many features has been used in the literature to compute the distance for classification.

2. BACKGROUND

Image Segmentation Using Extended Topological Active Nets Optimized by Scatter Search [1], introduces a novel optimization approach by embedding ETANs in a global search memetic framework, Scatter Search, thus considering multiple alternatives in the segmentation process using a very small solution population. With the aim of improving the accuracy of the segmentation results in a reasonable processing time, a global search-suitable internal energy term, a diversity function, a frequency memory population generator and two proper solution combination operators are introduced. In particular, these operators are effective in coalescing multiple meshes, a task previous global search methods for TAN optimization failed to accomplish.

Modified Gradient Search for Level Set Based Image Segmentation [2], e instead propose using two modified gradient descent methods, one using a momentum term and one based on resilient propagation. These methods are commonly used in the machine learning community. In a series of 2- D/3-D-experiments using real and synthetic data with ground truth, the modifications are shown to reduce the sensitivity for local optima and to increase the convergence rate. The parameter sensitivity is also investigated. The proposed methods are very simple modifications of the basic method, and are directly compatible with any type of level set implementation.

Reboost Image Segmentation using Genetic Algorithm [4], present a Improved Algorithm for Image Segmentation System for a RGB colour image, and presents a proposed efficient colour image segmentation algorithm based on evolutionary approach i. e. improved Genetic algorithm. The proposed technique, without any predefined parameters determines the optimum number of clusters for colour images. The optimal number of clusters is obtained by using maximum fitness value of population selection. The advantage of this method lies in the fact that no prior knowledge related to number of clusters is required to segment the color image. Proposed algorithm strongly supports the better quality of segmentation. Experiments on standard images have given the satisfactory and comparable results with other techniques.

A Noble Image Segmentation Using Local Area Splitting and Merging Method based on Intensity Change [6], adaptively changes pixel intensity during the process of region segmentation to the representative intensity of the adjacent sub-area of high homogeneity.

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Therefore, this method is not affected by the initial seed location, and it also eliminates pre-process, such as noise removal, because the pixel intensity is progressively stabilized to the average value of object. In addition, this method preserves the edges of segmented objects and reduces the phenomenon of excessive region merger by determining the direction of the next merger upon splitting a local area into small sub-areas.

Fuzzy entropy-based MR brain image segmentation using modified particle swarm optimization [7] performs image segmentation based on adaptive thresholding of the input MR images. The image is classified into two membership functions (MFs) of the fuzzy region: Z-function and S-function. The optimal parameters of these fuzzy MFs are obtained using modified particle swarm optimization (MPSO) algorithm. The objective function for obtaining the optimal fuzzy MF parameters is considered to be the maximum fuzzy entropy. Through a number of examples, The performance is compared with existing entropy based object segmentation approaches and the superiority of the proposed method is demonstrated.

The Potential of Double K-Means Clustering for Banana Image Segmentation [8], proposes a two-step k-means clustering technique was used to segment banana images in this study. The first k-means clustering image segmentation procedure could segment the contours of a banana finger and a banana hand from the background image. Adding the second k-means clustering could quantify the damage lesions and senescent spots on the banana surface.

A Hybrid Technique for Medical Image Segmentation [12], proposes a hybrid method for magnetic resonance (MR) image segmentation. We first remove impulsive noise inherent in MR images by utilizing a vector median filter. Subsequently, Otsu thresholding is used as an initial coarse segmentation method that finds the homogeneous regions of the input image. Finally, an enhanced suppressed fuzzy c-means is used to partition brain MR images into multiple segments, which employs an optimal suppression factor for the perfect clustering in the given data set.

Most of the approach discussed has the problem of false positive and overlapping, which tends us to design a novel approach for image segmentation.

3. PROPOSED METHOD:

The segmentation process has three stages namely: First preprocessing is performed, where the input image is performed with noise removal and image enhancement. Second, the multi variant features of input image are extracted and third energy estimation is performed. Finally the segmentation process is performed using energy estimated.

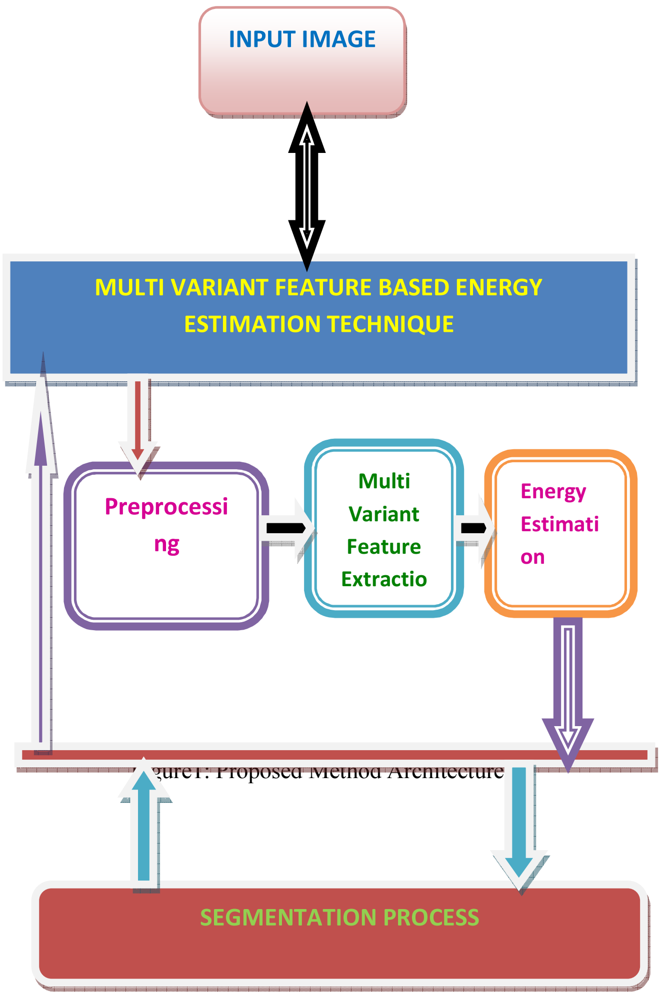

Figure1: Proposed Method Architecture.

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3.1 Preprocessing:

At the preprocessing stage we generate the gray scale values of the original image. The generated gray scale values are then normalized with the gray value distribution which makes the image with uniform gray distribution. This action is performed to bring the image for efficient processing task and we perform this by histogram equalization technique. The proposed method generates the histogram value of the image; we used 64 bit histogram for our purpose. The resultant value is used for the segmentation process. Based on the result of histogram equalization the image is segmented and reconstructed to provide the resultant image. The resultant image is displayed to the user and will be allowed to provide new threshold. Based on new threshold entered the clustering process and segmentation process will be repeated to provide new result. This methodology will be repeated until the user gets satisfied.

Algorithm:

Step1: start
Step2: read input image img, load possible intensity values Ivset= {0…256}..
Step3; convert image into gray scale
Compute size of image img [w, h] =size (img).
For each pixel from img
Img (i) = 0.2989 * R + 0.5870 * G + 0.1140 * B.
End
Step4: for each value in Ivset
Compute tp=total pixel having intensity value Ivset(i)/ total no of pixels.
End.
Step5: for each pixel p in image Img
Perform transformation by rounding the intensity values nearer.
T (k) = round (L-1) Σn=0-k pn
Compute probability distribution.
Pn – probability distribution
End
Step 6: stop.

3.2 Feature Extraction:

The preprocessed image is applied with feature extraction where the multi variant features are extracted. The feature extraction process extracts the following features namely, gray values, region mean of the pixel. For each pixel identified create a node which specifies set of gray values and their index on the image. Now the whole image is converted into set of nodes and each has its feature and index value. The extracted features are used to compute the energy estimation value of each pixel.

Algorithm:

step1: start

step2: initialize M,N, Node set G.

step3: read preprocessed image Img.

step4: for each pixel P_i from Img

Construct region matrix Rm.

$$Rm = \int_{M}^{N} (Pi(Img)m) \times (Pi(Img)n)$$

Compute mean gray value Gm = $\sum Pi(Rm)/($M×N)

Construct new node $G_i = \{P_{i,} Gm\}$.

$G = \Sigma G_{i(G)} + G_{i.}$

End.

step5: stop.

3.3 Segmentation:

The graph constructed in the feature extraction phase is selected for segmentation. From the graph each pixels node is selected and its energy is estimated using gray value of the pixel and region gray mean of the pixel computed in the earlier stage. The energy value shows how well a pixel carries the feature of neighboring pixels. A pixel will be assigned to a cluster only if the energy factor is within the threshold of energy factors of pixels present in the cluster. Segmentation is performed using computed energy factor and will be iterated till the user gets satisfied. The two nodes of graph is connected based on energy factor to form the group.

Algorithm:

step1: start
step2: initialize clusters C.
step3: Read feature graph G.
step4: read preprocessed image Img.
step5: for each cluster C_i of C
Select random Nodes from G.

$$C = \int_{1}^{N} Rand(G, 1..X)$$

X- Available nodes of G.
End.

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step6: for each cluster C_i from C

For each Node N_i from C_i

Compute Energy $E = \sqrt{Ni.Gm - \forall \frac{Ci.Ni.Gm}{\emptyset}}$

If E<= Eth then // Eth- Energy threshold

Assign N_i with C_i

Else

Continue;

End.

End

End.

step7: read user feed back

Read Eth.

Go to step 4.

step8: stop.

4. RESULTS AND DISCUSSION

The proposed method has been implemented and tested with Mat lab and we have used variety of data set to test the performance of the proposed approach. We use the well known simplicity dataset of Wang et al. These images are manually divided into 10 categories which are people, beaches, historian buildings, buses, dinosaurs, elephants, roses, horses, mountains, and foods. We conducted the performance comparison between our approach for image segmentation and two comparing algorithms which are K means algorithm and Gaussian Mixture Model (GMM) algorithm. For performing the K-means algorithm, we run 7 times of Automatic intensity graph noticed its average results.

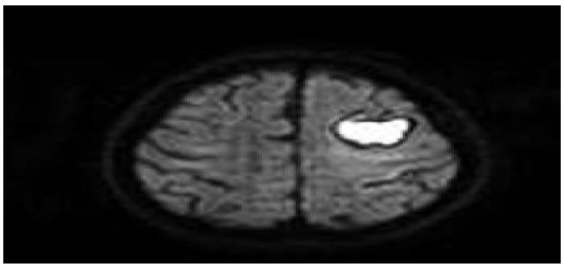


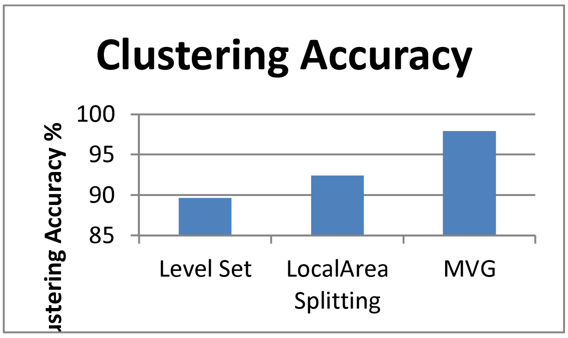
Figure2: Manually Segmented Image.

Figure3: Segmented Image With Automatic Graph.

Table1: Time Value Of Different Methods.

Method	Max. Time	Min.Time	Avg Time
LEVEL SET	24745	21068	22906
LOCAL AREA SPLITTING	6486	6047	6266
MVG	6046	5486	5766

The table1 shows the sum of times which is evaluated for 30 runs. It shows that the proposed Multi variant graph based segmentation has produced less time complexity than others.



Graph1: Comparison Of Clustering Accuracy

The graph1, shows the comparison result of accuracy between different methods and it shows that the proposed multi variant graph based segmentation approach has produced efficient clustering than other methods.

5. CONCLUSION

We proposed a user interactive multi variant feature graph based segmentation using energy value. The input image is preprocessed and extracts the features like gray value and mean gray distribution. The extracted features

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are converted into graph which is used at segmentation process. At the segmentation stage, each node from the graph is added to a cluster which is selected at random. Then we compute the energy factor for each of the node with the nodes of a cluster. Based on computed energy value a cluster will be assigned using energy threshold. This process will be performed iteratively till the user gets satisfied. The user will be able to modify the value of energy threshold, which increases the performance of the methodology. The proposed method has produced higher efficient segmentation quality and produces less space and time complexity.

REFERENCES

[1] Bova.N, Image Segmentation Using Extended Topological Active Nets Optimized by Scatter Search, IEEE Transaction in Computing Intelligence Magazine, vol:8, issue:1, pp: 16-32, 2013.

[2] Thord Anderson , Modified Gradient Search for Level Set Based Image Segmentation , IEEE Transactions on image processing, vol. 22, no. 2, February 2013.

[3] Faten Abu Shmmala, Color Based Image Segmentation using Different Versions of K-Means in two Spaces, Global Advanced Research Journal of Engineering, Technology and Innovation, Vol. 1(9) pp. 030-041, January, 2013.

[4] Ashutosh Jaiswal, Lavika Kurda and Vijai Singh. Article: Reboost Image Segmentation using Genetic Algorithm. International Journal of Computer Applications 69(19):1-7, May 2013.

[5] Pateek Gupta, Sargam Saxena, Sonali Singh, Saumya Dhami and Vijai Singh, "Color Image Segmentation: A State of the Art Survey", International Journal of Computational Intelligence Research Volume 8, Number 1 (2012), pp. 17-25

[6] Ryu Hyunki , A Noble Image Segmentation Using Local Area Splitting and Merging Method based on Intensity Change , International Journal of Software Engineering and Its Applications Vol.7, No.5 , pp.99-112 , 2013.

[7] R. Krishnapriya, Fuzzy entropy-based MR brain image segmentation using modified particle swarm optimization, International Journal of Imaging Systems and Technology Volume 23, Issue 4, pages 281–288, December 2013.

[8] Meng-han Hu1, The Potential of Double K-Means Clustering for Banana Image Segmentation, Journal of Food Process Engineering Volume 37, Issue 1, pages 10–18, February 2014.

[9] L. Grady and C. Alvino, “The piecewise smooth Mumford–Shah functional on an arbitrary graph,” IEEE Trans. Image Process., vol. 18, no. 11, pp. 2547–2561, Nov. 2009.

[10] G. Läthén, T. Andersson, R. Lenz, and M. Borga, “Momentum based optimization methods for level set segmentation,” in Proc. Int. Conf. Scale Space Variat. Meth. Comput. Vis., LNCS 5567. Jun. 2009, pp. 124–136.

[11] T. Andersson, G. Läthén, R. Lenz, and M. Borga, “A fast optimization method for level set segmentation,” in Proc. Scandinavian Conf. Image Anal., LNCS 5575. Jun. 2009, pp. 400–409.

[12] Alamgir Nyma, A Hybrid Technique for Medical Image Segmentation, Journal of Biomedicine and Biotechnology Volume 2012 (2012).

[13] C Mythili and V.kavitha. Article: Color Image Segmentation using ERKFCM. International Journal of Computer Applications 41(20):21-28, March 2012.

[14] Max mignotte, A label field fusion Bayesian model and its penalized maximum rand estimator for image segmentation, IEEE transaction on image processing, Vol 19, No. 6, June 2010.

[15] Outdoor Scene Image Segmentation Based on Background Recognition and Perceptual Organization, IEEE Transactions on Image Processing, Volume: 21, Issue: 3, Page(s):1007 – 1019, 2012.

[16] Thi Nhat Anh Nguyen, Robust Interactive Image Segmentation Using Convex Active Contours, IEEE Transaction on Image Processing, Volume: 21, Issue: 8, Page(s): 3734 – 3743, 2012.