International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 1 Issue 4, June - 2012

SEMANTIC REGION GROWING FOR MULTIVARIATE IMAGE SEGMENTATION USING ADAPTIVER EDGE PENALITY

J.Leela Mahendra Kumar, Assistant Professor; A.Vasavi , Assistant Professor;
And B.Praveena, Assistant Professor
Department of Electronics and Instrumentation Engineering
RGMCET,Nandyal

***Abstract*— Multivariate image segmentation is a challenging task, influenced by large intraclass variation that reduces class distinguish ability as well as increased feature space sparseness and solution space complexity that impose computational cost and degrade algorithmic robustness. To deal with these problems, a Markov random field (MRF) based multivariate segmentation algorithm called "multivariate iterative region growing using semantics" (MIRGS) is presented. In MIRGS, the impact of intraclass variation and computational cost are reduced using the MRF spatial context model incorporated with adaptive edge penalty and applied to regions. Semantic region growing starting from watershed over-segmentation and performed alternatively with segmentation gradually reduces the solution space size, which improves segmentation effectiveness. As a multivariate iterative algorithm, MIRGS is highly sensitive to initial conditions. To sup- press initialization sensitivity, it employs a region-level K -means (RKM) based initialization method, which consistently provides accurate initial conditions at low computational cost. Experiments show the superiority of RKM which are commonly used initialization methods. Segmentation tests on a variety of synthetic and natural multivariate images which demonstrate MIRGS.**

Keywords*— Initialization sensitivity, Markov random field(MRF), multilevel logistic (MLL) model, multivariate segmentation, region adjacency graph (RAG), semantic region growing, vector-valued image, watershed.

I. INTRODUCTION

Computer vision applications often require segmentation of digital imagery into semantically meaningful regions. The segmented regions can provide a basis for subsequent tasks such as object detection and recognition, scene understanding and content-based image retrieval. Therefore, ultimate performance depends upon segmentation accuracy. Rapid advances in image technologies lead to various types of digital images. Multivariate (vector-valued) imagery (e.g., colour images) depicts each site using a vector that characterizes the same scene from distinct aspects, where the number of vector elements is called the feature space dimension.Univariate imagery (e.g., grayscale images) can be regarded as a special multivariate case in which each site is depicted by a scalar. Multivariate image segmentation has been widely applied in diverse fields. Although theoretically feasible to extend many univariate segmentation techniques to their multivariate counterparts, practical performance is influenced by the multivariate nature of the image. Intra class variation is typically present since semantically meaningful regions (classes) are often inhomogeneous due to scene characteristics, imaging environment, and image noise. Large intraclass variation usually reduces class distinguish ability which degrades segmentation performance. Multivariate imagery is especially sensitive to large intraclass variation since every component image is a variation contributor. Moreover, computational cost of segmentation algorithms increases while algorithmic robustness tends to decrease with increasing feature space sparseness and solution space complexity. Markov random field (MRF) based image segmentation is advocated for its intrinsic capability of reducing the impact of intraclass variation using spatial context information. We built an iterative region growing using semantics (IRGS) algorithm for univariate image segmentation, which incorporates edge information with the MRF model. We present a region-level MRF-based segmentation algorithm named multivariate IRGS (MIRGS), which advances the merits of the univariate IRGS to deal with multivariate imagery. Similar to IRGS, MIRGS is also sensitive to initial conditions, which becomes more pronounced as the feature space dimension increases.

In this paper, we have implemented a method for Semantic Region Growing for Multivariate Image Segmentation using Adaptiver Edge Penality. The Block diagram is discussed in section II. In section III, Background described. Section IV covers MIRGS Properties Section V covers Simulation Results. Section VI concludes the study.

II. BLOCK DIAGRAM

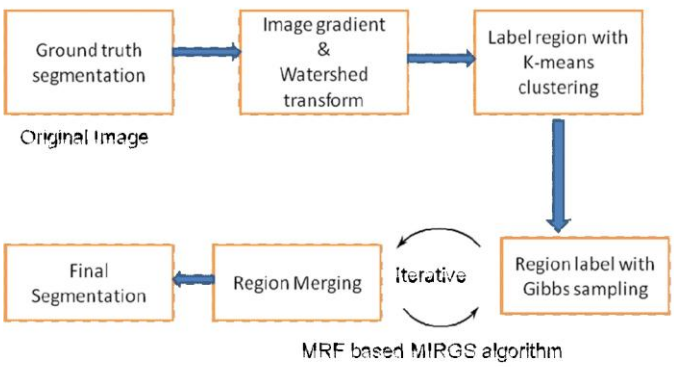


Figure: Block Diagram of Multivariate Image Segmentation Process.

III.BACKGROUND

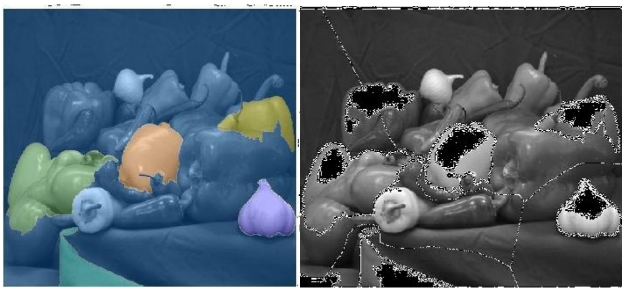
Separating touching objects in an image is one of the most difficult image processing operations. The watershed transform is often applied to this problem. The watershed transform finds "catchment basins" and "watershed ridge lines" in an image by treating it as a surface where light pixels are high and dark pixels are low

A. Marker controlled Watershed segmentation

Segmentation using the watershed transforms works well if you can identify, or "mark," foreground objects & background locations.

Marker-controlled watershed segmentation follows this basic procedure:

1. Compute a segmentation function. This is an image whose dark regions are the objects you are trying to segment.
2. Compute foreground markers. These are connected blobs of pixels within each of the objects.
3. Compute background markers. These are pixels that are not part of any object.
4. Modify the segmentation function so that it only has minima at the foreground and background marker locations.
5. Compute the watershed transform of the modified segmentation function.



Simulation:Marker controlled water segmentation

B. Region Level K-means Clustering:

Clustering is a way to separate group of objects. K-means clustering treats each object as having s location in space.

It finds partions such that objects within each cluster are as close to each other as possible and as far from objects in other cluster as possible. In K-means clustering we require to specify the number of cluster are to be portioned and a distance metric to how close the 2 objects are to each other.

Since the colour information exists in the a*b space and objects are pixels with a* * b* values.

Here we use k-means algorithm to cluster the objects into two cluster regions using Euclidean distance metric.

STEPS:

1. Convert the image from RGB color space to L*a*b color space
2. Classify the color in a*b space using k-means clustering.
3. Label each pixel in the image using the results from K

L*a*b color space is derived from co-coordinator values.

L space consists of luminosity layer 'L*' **a** space consists of Chromaticity layer

indicating whose color falls along 2 color (R-G)

b space consists of Chromaticity layer indicating whose color falls along the blue and yellow axis All of the color information is in the a* and b* layers .We can measure the difference between two colors using the Euclidean distance metric

Simulation: K-means clustering

C. Labeling with Gibbs Sampling:

Once the initial K-means segmentation is generated, MIRGS enters the iterative portion of the algorithm. The goal is to find the optimal labelling of each watershed region. This is done by finding a configuration of labels that globally minimizes a cost function. MIRGS iteratively performs labelling of the watershed regions, followed by region-merging. At each iteration, an intermediate segmentation result is generated. Region-merging reduces the number of nodes in the RAG by combining adjacent regions. This makes the labelling process in the subsequent iterations more efficient as fewer nodes have to be considered. Additionally, the solution process is not as likely to be trapped in a local minimum when regions are merged together. The number of iterations for MIRGS is set to a fixed value by the user and 100 iterations is the number typically used. The cost function that MIRGS minimizes in order to produce the optimal segmentation x^r* is the following.

$$x^{r^*} = \arg\min_{x^r \in X^r} E_f + E_s$$

Ef is a feature model and Es is spatial context model energy defined

Ef defined as follows

$$E_f = \frac{1}{2c}\sum_{i=1}^{n}\sum_{s_v\in\Omega_s}\sum_{s\in s_v}\log\,|\Sigma_i|\;+(Y_{s-}\mu_i)^T\,\Sigma_i^{-1}(Y_{s-}\mu_i)$$

Es defined as follows

$$E_s = \beta\sum_{i=1}^{n-1}\sum_{j-i+1}^{n}\sum_{s\in\partial\Omega_i\cap\partial\Omega_j}^{n} g(\nabla_s)$$

G(delta(s)) is a edge penalty is defined as

$$g(\nabla_s) = \exp\left[-\left(\frac{\nabla_s}{k}\right)^2\right]$$

Where delta(s) is a normalised image gradient.
MIRGS incorporates the method to derive beta

from the data and is implemented as

$$\beta = C_1\frac{J/C_2}{1+J/C_2}\beta_0$$

where J is the minimum Fisher criterion between any two classes in the image according to the current segmentation result (i.e., it is the Fisher criterion between the two classes that are least separable from each other), C1 and C2 are user-defined constants and is an intermediate parameter.

D.Region Merging:

After the labeling process is completed for all nodes, region merging is performed in a greedy fashion. The process only considers all pairs of adjacent regions which have the same class. Let ∂E be the total change of the energy in Equation if a pair of such regions is merged. The algorithm will merge the pair of regions that has the smallest negative ∂E and update the RAG. This continues until the smallest ∂E is non-negative.

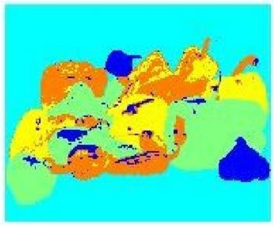
When region-merging is complete, the algorithm will go back to Step 3 until the desired number of iterations is reached, at which point the final segmentation will be produced.

IV.MIRGS PROPERTIES

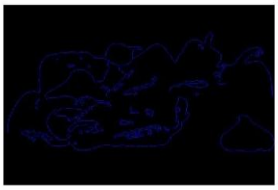
The multivariate extension from IRGS to MIRGS involves both major and minor changes. MIRGS inherits many attractive properties from the univariate IRGS:

- MIRGS uses a monotonically decreasing edge penalty function with the region-level MLL model.
- M I R G S changes edge penalty at each iteration to generate a sequence of spatial context models.
- MIRGS performs on a hierarchical RAG with the bottom-up no increasing vertex number, which gradually reduces the solution space size to improve segmentation effectiveness

V.SIMULATION RESULTS



Original Image



MIRGS based Image

Figure:
Segmentation of the image using MIRGS algorithm. Original image is segmented using the steps which gives segmented image .Class boundaries are outlined in distinct colors.

VI.CONCLUSION

We present a MRF-based multivariate segmentation algorithm named MIRGS, which extends the applicability of IRGS to multivariate images while inheriting the merits of IRGS. To suppress initialization sensitivity, MIRGS uses a RKM-based initialization method, which consistently provides accurate initial conditions at low computational cost. The superiority of RKM relative initialization schemes has been demonstrated on images with different feature space dimensions.

For a variety of synthetic and natural multivariate images, MIRGS consistently achieves the highest segmentation accuracy

. Therefore, fast methods to establish the hierarchical RAG are important for future investigation. Moreover, to automatically determine the number of classes instead of pre specifying it as an algorithmic parameter is desirable. In addition, MIRGS mentioned in this paper is performed in an unsupervised manner, which does not take into account any domain knowledge. However, the domain knowledge can be easily incorporated into and used in to produce the supervised MIRGS, which deserves future investigation.

REFERENCES:

[1].Q.Yu and D.A.Clausi*,"SAR sea-ice image analysis based on iterative region growing using semantics,"IEEE.Trans*.Geoscience,Remote Sens., vol.45, no.12, pp.3919-393 Dec 2007.

[2]S.Z.Li, *Markov Random Field Modeling in Image Analysis,* 2nd ed.New York: Springer-Verlag, 2001.

[3] Q.Yu and D.A.Clausi*,"IRGS:Image Segmentation using edge penalties & Region growing,"*IEEE Trans, Patteren Ana Mach.Intell. Vol.30, no.12, pp.2126- 2139 Dec.2008

[4] J.C.Noordam, W.H.A.M.van dem Broek, & L.M.C.Buydens,"*Multivariate image Seg with cluster size insensitive Fuzzy c-means,*" chemomet. Intell.Lab.Syst Vol.64, no.1, pp.65-78, Oct.2002.

[5] H.Deng and D.A.Clausi and "*Unsupervised Image segmentation using a Simple MRF Model with new implementation scheme.Pattern recg* vol 37,no.12,pp,2323-2335,2004

[6]G.S.Xia , C.He,and H.Sun "*Integration SAR Image segmentation method using markov Random filed on region adajency graph*"IET Radar, sonar nav,vol.1,no:5,pp:348- 354.2007

[7]P.YU,"*Segmentation of Radar SAT 2-Dual Polarization Sea Ice Imagery*"Masters thesis university waterloo,ON,Canada aug:2009