International Journal of Scientific and Research Publications, Volume 3, Issue 1, January 2013 1
ISSN 2250-3153

Scaling Constant Estimation for Texture Segmentation using Level Sets

K M Sadyojatha *, Vinayadatt V Kohir **, Subhash Kulkarni ***

[*] Ballari Institute of Technology and Management, Bellary, Karnataka, India,
[**] PDA college of Engineering, Gulbarga, Karnataka, India,
[***] PES institute of Technology, Bangalore, Karnataka, India,

Abstract- Proposed work is aimed at finding a method to estimate a scaling parameter λ because of which minor object irregularities in the target texture image are ignored by the level set function during the process of curve evolution. Here the texture segmentation is achieved by embedding the statistical moment features in to the Level set frame work implemented as per Chan – Vese approach. The scaling parameter estimated here is used for emphasizing the variances of intensities of inside or outside regions of the evolving curve, which is estimated from the histograms of the extracted moment features. Reasonably correct values of λ are estimated and are substantiated by the results presented in the further sections.
.

Index Terms- Level sets, Moments, Scaling parameter, Texture segmentation

I. INTRODUCTION

Segmentation techniques are normally either edge based or region based. The separation of different regions of an image is based on the dissimilarities between the regions in edge based techniques, were as the similarities within the region becomes the basis in case of region based techniques. The image containing texture regions has neither a well-defined edge nor a homogeneous distribution of intensities within the same class region. Hence the segmentation of such image is challenging for either of the two approaches mentioned above. If the distribution of intensities of an image is such that the regions are distinct as shown in fig 1(a), thresh holding can very conveniently separate the different regions. But such a situation is scantly seen as far as the textured images are concerned. Normally the distributions of intensities of different regions will be overlapping as shown in fig 1(b), where the pattern recognition techniques like thresh holding or clustering fail to partition the different regions of such image. In case of K-means, the Gaussian parameters are iteratively computed but the connectedness of the different partitions after segmentation is not ensured.[6] Under such circumstances a shift in the approach from pattern recognition techniques to some image processing techniques is required. Therefore, as an alternative, deformable models via level sets along with statistical moment features is used in this proposed work.[7].

1a **1b**

Figure1a and 1b: Distribution of intensities Vs frequency of occurence

In this above context the present paper is poised on using of simple moment descriptors viz. mean, standard deviation and 3rd order moment of texture images over a predefined neighbourhood. This reduces the computational complexity and yet yielding irredundant texture features [7] when compared to more commonly used filter bank schemes like Gabor filters [4].

The features thus selected present a favourable ambience for segmenting an image. The conventional segmentation tool works well when the between class scatter is higher than a threshold level forcing the segmentation result to be erroneous. One solution to the problem is to include spatial neighbourhood information along with the feature selected. The inevitable option is to use deformable model as a tool. Level set frame work is implemented as per Chan – Vese approach [5][11].

In the simplest case, assume that an image I defined on Ω is composed of two regions separated by initialized model curve with homogeneous intensity values c_i and c_o. Given a curve C that corresponds to boundary descriptor of the image I, homogeneity – based functional is introduced as

$$E(C) = \int_{insideC} | I - c_i |^2 \, d\Omega + \int_{outsideC} | I - c_o |^2 \, d\Omega \qquad (1)$$

where c_i and c_o are the average image intensities inside and outside of the model propagating curve C respectively. Assuming q to be the piece wise approximated model having intensity c_i inside C and c_o outside C, it is easy to observe that q can be represented as

$$q = c_i H(\phi) + c_o (1 - H(\phi)) \qquad (2)$$

where the Heaviside function H (Φ) is defined as

$$H(\phi) = \begin{cases} 1, \phi > 0 \\ 0, \phi \leq 0 \end{cases}$$

II THE λ PARAMETER

With the functional in equation (1) the boundary between regions is defined by its extremum. To keep the curve functional continuously differentiable during evolution, regularizing terms based on the length and the area metrics of the curve are added.

$$E(c_i, c_o, C) = \lambda_i \int_{insideC} | I - c_i |^2 d\Omega + \lambda_o \int_{outsideC} | I - c_o |^2 \, d\Omega + \mu \, length(C) + \nu \, area(C) \qquad (3)$$

Translating the energy functional in equation (3) to a higher dimensional level set function, one obtains

$$E(c_i, c_o, C) = \lambda_i \int_{\Omega} | I - c_i |^2 \, H(\phi) d\Omega + \lambda_o \int_{\Omega} | I - c_o |^2 \, (1 - H(\phi)) d\Omega + \mu \int_{\Omega} \delta(\phi) | \nabla \phi | \, d\Omega + \nu \int_{\Omega} H(\phi) d\Omega \qquad (4)$$

This functional in equation (2) when subjected to minimization via Eulerian converts into motion PDE resulting into propagation of model curve.

μ ,ν, λ_i, λ_o are positive scaling constants for the length , inside area, inside and outside variances respectively.[8]. The values of λi, and λ_o included in the proposed model decide the contribution of variances of inner and outer regions respectively to control the evolution of model curve.

In the present work the values of the λi,and λ_o computed from the histograms of the feature images. As these parameters are used as scaling constants, they basically represent the variances of intensity distributions inside and outside of the evolving curve. Histograms of moment feature of an example texture combination are shown in figure (2).

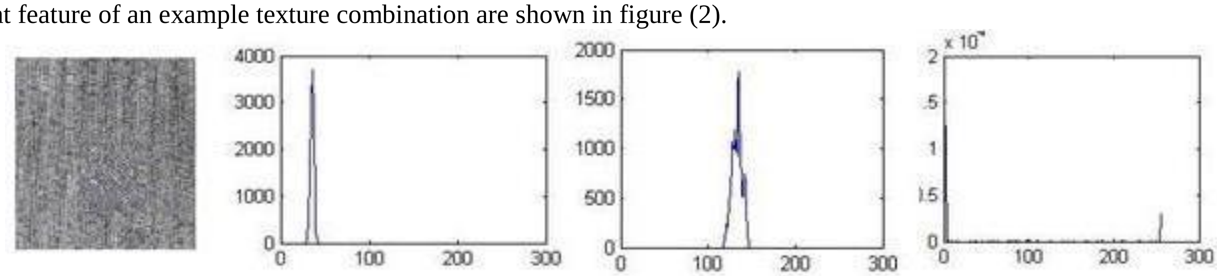


Figure2: from left-original image with combination of two textures, histogram of mean ,varience and third moment of image.

It is difficult to identify the two texture regions distinctly from any of the histograms pertaining to mean or variance or the third moment as they are overlapping on one another. It can be read from the histograms that there are some dominant peaks and some of the peaks are comparatively small. These small peaks represent the object irregularities which are to be ignored by the evolving curve during the process of segmentation. One can logically decipher from the histograms that the width of the part of the histogram is the index of the variance within the respective region. i.e. more the width of the part of histogram pertaining to a region, more object irregularities within that region. Therefore higher the irregularities higher should be the tolerance so that the evolving curve shall not stop at the local minima. In a nut shell if some region is inside the evolving curve and the irregularities are more, a higher λi than λ_o value should be selected and vice versa.

It is found possible to compute the ratio of λ_i,and λ_o based on the histograms of the feature sets. The histogram of the appropriate moment, which is used for segmentation is considered for estimation of λ_i,and λ_o values. First the positions of the peaks are to be found for estimating the width of one part. This can be simply done by finding the zero crossings and computing the distance between two zero crossings in the differentiated version of the histogram which is shown in figure (3).

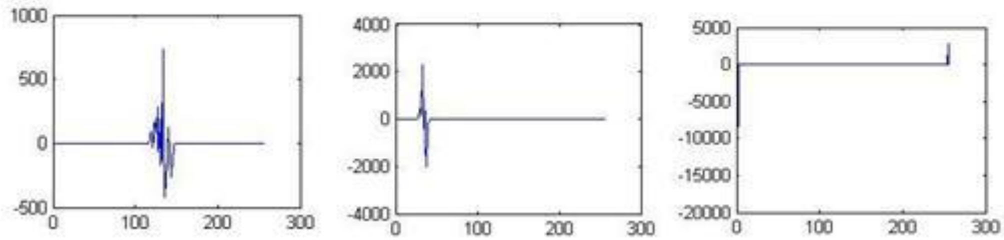


Figure3: Histograms' peaks represented as zero crossings for mean, variance and third moment

The ratio of widths between the dominant positive peak and the next negetive peak to the width between the dominant negative peak and the nest positive peak is taken as the ratio of λ_i,and $\lambda_{o.}$ The zero crossing positions of the above figure are presented below.

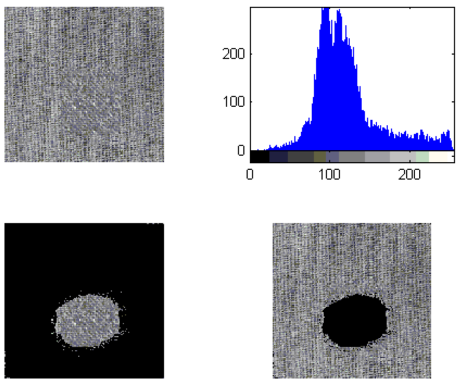
Zero crossings of positive peaks for the first histogram(mean): 120 127 130 134 141

Zero crossings of negative peaks for the first histogram(mean): 121 129 132 139

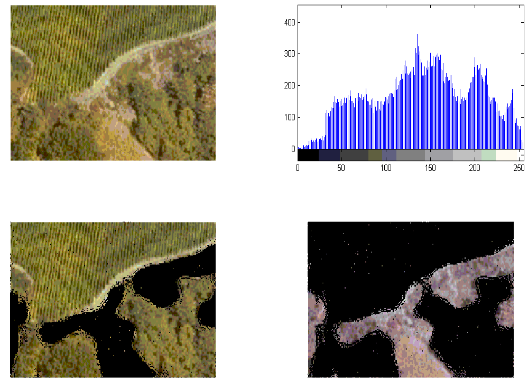
The ratio of λ_i,and λ_o from the above values can be computed as 5/9 which is 0.55 and if λ_1 is taken as 0.1 and λ_o can be calculated as 0.2.

III RESULTS AND DISCUSSIONS

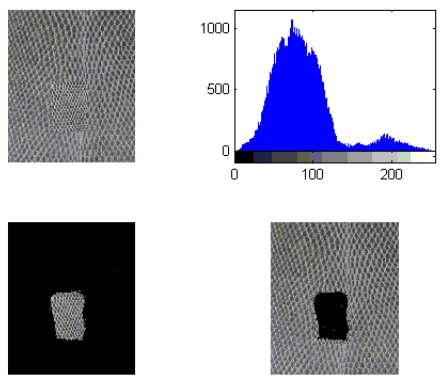
The results are obtained using the motion PDE as mentioned above as in equation (5) and the λ values calculated as per the procedure explained in the previous section. Some of the results are presented below with the λ values used.



a: λ_i= 0.1 and λ_o= 0.2



b: λ_i= 0.3 and λ_o= 0.08



c: λ_i= 0.1 and λ_o= 0.6

Figure4(a),(b),(c):Top of each result- original image , histogram and bottom two images- segmented portions.

The results presented in (a) and (c) for combination of two texture images extracted from Brodatz data base and (c) is a natural image containing textured regions. Results are also shown with texture regions having holes within and also with irregular boundaries.

IV .CONCLUSION

Intrinsic competence of the level set framework to segment the image in spite of overlapping features and computationally less intensive feature descriptors, when united result into efficient and robust segmentation framework which is evident from the results which are presented above. The main novelty of the work is finding a method for estimation of λ values helping the frame work to function totally unsupervised way and the unification of pattern recognition and image processing techniques as mentioned above. This proposed technique can be a better alternative to the computationally and time intensive conventional texture segmentation techniques such as Gabor filters or Wavelets [1][2][3][10].The present paper deals with segmentation of two layer textures. Further segmentation of multiple layer textures can be explored [9].

REFERENCES

[1] A.C. Bovik, M.Clark, and W.S.Geisler, "Multi channel texture analysis using localized spatial filters", IEEE trans. Pattern Anal. Mach Intell., Vol.12, No.1, pp 55 – 73, Jan (1990).

[2] A.Laine and J.Fan, "Texture classification by wave let packet signatures," IEEE trans, pattern Anal. Mach. Intell., Vol.15, No.11. pp.1186-1191, Nov.(1993).

[3] A.Laine and J.Fan, "Texture classification by wave let packet signatures," IEEE trans, pattern Anal. Mach. Intell., Vol.15, No.11. pp.1186-1191, Nov.(1993).B. Smith, "An approach to graphs of linear forms (Unpublished work style)," unpublished.

[4] D.Dunn and W.Higgins, "Optimal Gabor filters for texture segmentation," IEEE trans, image process., Vol.4, No.7. pp.947-964, July (1995).

[5] Mumford D. and Shah J., "Optimal approximation by piece wise smooth function and associated variational problems". Commu^{n}.Pure Appl. Math,42, , 577-685 (1989).

[6] R.Conners and C.Harlow, "A theoretical comparison of texture algorithms," IEEE trans. Pattern Anal. Mach. Intell, Vol.2, No.PAMI-3, pp.204-222, May (1980).

[7] Sadyojatha K.M. and Subhash Kulkarni "Texture Segmentation Using Level Sets,", ICCR 2008, Mysore, India, 168-174, 2008.

[8] Sandeep V.M. and Subhash Kulkarni "Efficient Hierarchical approach for perceptual segmentation using Multi-phase Level Sets,", IEEE's ICSIP2006, Hubli, India, 692-697, (2006).

[9] Sandeep V.M., Subhash S.K., Natural histogram portioning based on invariantmulti-phase level set, IEEEs ADCOM2006, NITK, Surathkal, India, 314-317,2006

[10] T.Chang and C.Kuo, "Texture analysis and classification with tree structured wave let transform", IEEE trans. image process Vol.11, No.2, pp 429 – 441, Oct. (1993).

[11] T.F.Chan, L.A.Vese, Active contours without edges, IEEE trans. on image processing, 10, , 266-276, (2001).

Correspondence Author – Sadyojatha K M , saddukm@gmail.com, +91 9448020788

.