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Evaluation of Classification in Markov Random Field (MRF) Segmented Images in the Presence of Gaussian Noise

Vishal Kalra[1], Sumit Kaushik[2] and Preeti Kaushik[3]

[1]M.Tech Scholar, [23] A.P., GNIT, Mullana, India

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Abstract

The major objective of computer vision is to enable the machine to understand the world of visual observation through the processing of digital signals. Such an interpretation for the machine is done by extracting useful information from the digital signals and performing complex computation. Energy minimization in image segmentation is a distinguished approach in computer vision. One of the best suited model for image segmentation is Markov Random Fields (MRF). In this paper segmentation is carried out with the help of MRF which estimates the classification level in each region of the image in the presence of Gaussian Noise

Keywords: *MRF, Gibbs distribution pixels, Cliques.*

1. Introduction

In image segmentation generally extraction of features from the input image is carried out. The image is divided in to pixels and each pixel in the image has a feature vector, for further processing in each pixel of an image is assigned a label that is denoted by ω_s and the entire set of labels is denoted by Λ. Each pixel is assigned a label $w_s \in \Lambda$. And the entire image can be represented as following:

$$\omega = \{\omega_s : s \in S\}$$

for an image with size NXM, the total number of possible labeling are Λ^{NXM}. In this paper we have defined a technique in which a user selects multiple regions from an image. In the selected image regions may be uniform as well as Non Uniform in the form of ratio of various colors in the each selected region and performs segmentation to extract useful information out of it and also performs energy minimization. The major objective of this approach is to increase the classification level in the image that is affected by Gaussian noise. For every region under various noise levels Classification and Misclassification level is calculated to validate MRF and Gibbs Equation. The outline of this paper is as follows. In Section 2 we give a brief description of various past work associated with Image segmentation. Section 3 gives the introduction to a Markov random field & Gibbs distribution defined on our region-based image model. Section 4 gives out the experiment result and the conclusions are listed in section 5.

2. Related Work

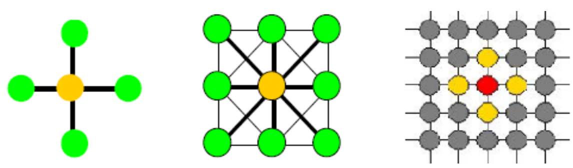
K Vani Sree *et al* [7] expressed that image segmentation aims at extracting meaningful objects lying in images either by dividing images into contiguous semantic regions, or by extracting one or more specific objects in images such as medical structures. The image segmentation task is in general very difficult to achieve since natural images are diverse, complex and the way we perceive them vary according to individuals.

Kato, Zoltan *et al* [1] expressed segmentation of grayscale images where regions are formed by spatial clusters of pixels with similar intensity.

Chaohui Wang *et al* [5] discussed the MRF model with respect to the forming of multi label MRFs and using graph by first introducing auxiliary binary variables each corresponding to apossible
label of a node and then deriving a min-cut problem

3. MRF Based Image Segmentation

For each pixel some surrounding pixels are defined as neighbors and are further categorized as first order and second order neighbours.



[1] Fig 3(a) Fig 3(b)

Fig.3 (a) First order neighbors) 3(b) Second order neighbors

The labeling field X can be modeled as markov random field (MRF) if the following conditions are satisfied

1. For all $\omega \in \Omega$: $P(X = \omega) > 0$
2. For every $s, \in S$ and $\omega \in \Omega$
3. $P(\omega_s \mid \omega_r, r \neq s) = P(\omega_s \mid \omega_r, r \in \mid N_s)$

Where N_s denotes the number of pixels

According to Hammersley-Clifford Theorem a random field is a MRF if and only if P(ω) follows a Gibbs distribution.

$$P(\omega)= \frac{1}{z} \exp(-U(\omega)) = \frac{1}{z} \exp(-\sum V_c(\omega))$$

Here z in the above equation is a normalization constant which has the value equal to exp (-U(ω)) . This theorem states that MRF models can be easily defined with the help of clique potentials. Let us define each clique of the image by 'c', then clique potential potential can be defined as $V_c(\omega)$, where ω is the configuration of the labeling field. The sum of potentials of all cliques gives us the energy U (ω)of the configuration ω

$$U(\omega) = \sum_{c=C} Vc(\omega) = \sum_{i=C1} Vc1(\omega i) + \sum_{(i,j)=C2} Vc2(\omega i, \omega j) + \cdots$$

4. Gibbs Distribution

Pixel labels are represented by guassian distribution

$$\boldsymbol{P(fs|\omega s) = \frac{1}{\sqrt{2\pi\sigma_{\omega s}}} \exp(-(f_s - \mu_{ws})^{\wedge 2}/2\sigma_{ws}^2}$$

Clique potentials[2]: are cateorised in to singleton &doubleton images. Singleton potentials are proportional to likelihood of the features given ω: log(P(f | ω))
Doubleton potentials favors similar labels at neighboring pixels – smoothness prior

$$\boldsymbol{V_{c2}(i,j) = \beta\delta(\omega_i, \omega_j) = \begin{Bmatrix} -\beta \ \ if \ \omega_i = \omega_j \\ +\beta \ if \ \omega_i \neq \omega_j \end{Bmatrix}}$$

Where β represents doubleton potential it is clear from the above equation that as β increases the regions become more homogenous. This potential is less dependent upon input and can be fixed as priori.

5. Experimental results

In this section, we illustrate the efficiency and power of our approach and make a comparison with the traditional segmentation methods using two images:

1. Lena coloured image with size 512 X 512. (see fig1(a))
2. Cameraman coloured image with size 512X512.(see fig1(b))

For both the images mentioned above we have performed image segmentation by varying the noise content from 10% to 80%. The dominant colour in each region of the image is estimated by segmenting the given image with under noise free condition. It is notified that as noise level in the image increases, the classification decreases.

Fig 5(c) and 5(d) shows the presence of Gaussian noise in the Lena and Camera man image. Result analysis is shown by the graphical representation in which classification of each region is shown under various noise levels it. The results are shown in figure 5(e) for Lena and Cameraman image respectively. It is clear from the graphs as the noise content increases the level of classification decreases at 60% the classification is very less and at 80% noise level the classification fails.

Fig. 5 (a)

Fig. 5 (c)

Fig. 5 (b)

Fig. 5 (d)

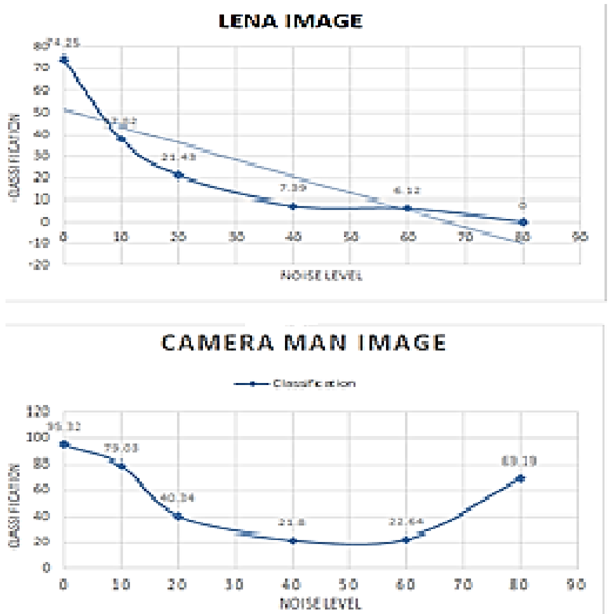


Fig. 5(e) Experimental Results

Conclusion

It is clear from the results studied above that MRF performs a better image segmentation in the presence of Gaussian Noise. In the current work two images were taken and two Regions were chosen : Uniform Regions and Non- Uniform Regions. Region 1 and 3 (indicated by R1 and R3) in cameraman image and region 1 & 4 (R1&R4) in Lena image are marked as uniform regions. A general result shows that classification in the in the presence of noise decreases. It shows that in early stages when the percentage of noise is less good segmentation results but as the percentage of noise increases up to 80%, MRF fails to perform classification at 60% the visualization of the classification is poor.

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