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Improved Hidden Markov Random Field and its Expectation Maximization Algorithm for Image Segmentation

Pooja Kalra[1], Amit Sharma[2]

[1]Student, CSE Department, Ambala College of Engineering & Applied Research, Devsthali, Ambala

[2]Assistant Professor, Department of Computer Science & Engineering, Devsthali, Ambala

Abstract: ***Image segmentation is used to understand images and extract information or objects from them. Unsupervised image segmentation is an incomplete data problem as the number of class labels and model parameters are unknown. In this paper, we have analyzed HMRF that defines a probability measure on the set of all possible labels and select the most likely one for unsupervised image segmentation. As HMRF model parameters are unknown, to handle this problem Expectation Maximization algorithm is used. The modulated intensity along with edge map, gray level pixel of intensities and initial labels from K-means information is provided to HMRF-EM algorithm for segmentation. The results obtained by proposed Improved HMRF-EM algorithm are compared with the HMRF-EM algorithm. on the basis of PSNR and Improved HMRF-EM will result in better segmentation quality.***

Keywords: Image segmentation, HMRF, Expectation Maximization, RMSC, PSNR.

1. Introduction

Images are considered as the convenient medium of conveying information, in the field of pattern recognition, object extraction and computer vision. In digital image processing, input and output data are images and in addition, also include the processes that extract the attributes from images, up to and including the detection of individual object. By understanding images the information extracted from them can be used for various tasks like: authentication and identification of the owner, detection of cancerous cells, recognition malign tissues from body scans, and identification of an airport from remote sensing data. In order to understand images and extract information or objects, a method is needed, image segmentation fulfill these requirements. In computer vision, **image segmentation** is the process of partitioning a digital image into multiple segments (sets of pixels, also called as super pixels). The aim of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. The segmentation of 2D and 3D images is an important first step for a variety of image analysis and visualization tasks. Hence, image segmentation is one of the early vision problems and has a wide application domain. The segmentation problem can be categorized as (i) supervised and (ii) unsupervised approach. In supervised framework, the model parameters are assumed to be known a priori. These model parameters are used for estimating the pixel labels in segmentation framework. In unsupervised framework, the number of class labels and the model parameters are unknown. Estimation of image labels as well as model parameters is required simultaneously. Since the image label estimation depends upon the optimal set of parameters, the unsupervised image segmentation is viewed as an incomplete data problem. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. It provides additional information about the contents of an image by identifying edges and regions of similar color, intensity and texture, while simplifying the image from thousands of pixels to less than a few hundred segments. Each of the pixels in a region is similar with respect to some characteristic or computed property.

1.1 Image Models for Segmentation

In recent years, stochastic models have become more popular in image processing. Out of the various stochastic models, Markov random field (MRF) model provides a better framework for many complex problems in image segmentation. This is due to the fact that, MRF model is based on the notion of neighborhood structure and therefore, helps in understanding global interaction through local spatial interactions. Moreover, the global interaction is governed by Gibbs distribution. This started with the influential work of Geman & Geman who linked via statistical mechanics between mechanical systems and probability theory. The distribution for a single variable at a particular site is conditioned on the configuration of a predefined neighborhood surrounding that site. Markov Random Field (MRF) based methods have been widely used by researchers [1]. The extension of an observable Markov Model is the Hidden Markov Model (HMM). Here the observation is a probabilistic function (discrete or continuous) of a state. All observations are dependent on the state that generated them, not on the neighboring observations. HMM is a finite set of states, each of which is associated with a probability distribution. In a particular state an outcome or observation can be generated, according to the associated probability distribution. It is only the outcome, not the state visible to an external observer and therefore states are “hidden” to outside; hence the name Hidden Markov Model. This model is specifically useful where the data is hidden. A special case of HMM is that, the underlying stochastic process is considered as MRF instead of a Markov chain and therefore not restricted to one dimension. This special case is referred to as Hidden Markov Random Field (HMRF) model. The segmentation only relies on the histogram of the data and therefore is sensitive to noise and other artifacts or variations. To overcome this limitation, a hidden Markov random field (HMRF) is derived [14]. The HMRF model is based on the Markov random field theory, in which the spatial information is encoded through a neighborhood system. Hidden Markov random field (HMRF) model is a stochastic process generated by a Markov random field whose state sequence cannot be observed directly but can be observed through observations. The advantage of the HMRF model derives from the way in which the spatial information is encoded through the mutual influences of neighboring pixels. Mathematically, an HMRF model is characterized by the following:

- Hidden random field
- Observable random field
- Conditional independence

The HMRF model is more flexible for image modeling in the sense that it has the ability to encode both the statistical and spatial properties of an image.

2. Related Work

The image segmentation is a challenging problem that has received an enormous amount of attention by many researchers. For appropriate analysis, different image models have been proposed for taking care of spatial intrinsic characteristics. The popular stochastic model provides the better framework for many complex problems in image segmentation is Markov Random Field (MRF) model. S.A Barker *et al.* [11] presented an unsupervised image segmentation algorithm based on Markov Random Field for noisy images. The algorithm finds the most likely number of classes, their associated model parameters and generates the corresponding segmentation of the image into these classes. This is done according to MAP criterion. Yangxing LIU et al. [12] proposed an MRF Model Based Algorithm of Triangular Shape Object Detection in Color Images in 2006 and in 2007 provides an algorithm for detecting multiple rectangular shape objects called Markov Random Field (MRF) [13]. Firstly, for obtaining accurate edge pixel gradient information they use an elaborate edge detection algorithm. Then from the edge map line segments are extracted and some neighboring parallel segments are merged into a single line segment. Finally with MRF Model built on line segments is used for labeling all segments lying on the boundary of unknown triangular objects. Zhang *et al.* proposed Hidden Markov Random Field (HMRF) model to achieve brain MR image segmentation in unsupervised framework [14]. The segmentation obtained by Zhang's approach greatly depends upon the proper choice of initial model parameters. Quan Wang [7] implements Hidden Markov Random Field Model and its Expectation-Maximization Algorithm. Firstly, Binary edge map information is obtained by performing canny edge detection on original image and gray-level intensities of pixels are obtained by performing Gaussian blur on the original image. Then K-means clustering is applied on gray-level intensities of pixels. The initial labels obtained from K-means are not smooth and have morphological holes and therefore HMRF-EM is applied to refine the labels.

3. Problem Definition

Image Segmentation is an important task within the field of computer vision and image processing. Image Segmentation is the process of segregating an image into one or multiple segments that change the representation of an image into objects of interest, which then becomes more meaningful and can be easily analyzed. HMRF-EM algorithm is used for image segmentation. In this algorithm firstly edge map information is obtained by using some edge detection algorithm and Gray level pixel of intensities are obtained by blurring the image. After that K-means are applied on Gray level pixel of intensities to get the initial labels. And then binary edge map, Gray level pixel of intensities and initial label obtained from K-means information is provided to HMRF-EM algorithm to refine the labels. If some extra information along with these is provided to HMRF-EM algorithm then better segmentation results on more complicated images can be obtained. So, we have decided to provide Modulated Intensity along with Edge map, Gaussian blur and initial labels from K-means as input to HMRF-EM to improve the segmentation quality. Then Comparative analysis is done to show the quality enhancement of proposed work.

4. Methodology Approach

To show the methodology various steps have been followed as shown in Figure 1. In the first step, input an image for segmentation. The next step is to obtain binary edge map is by performing canny edge detection on the original image. Among the edge detection methods developed so far, canny edge detection algorithm is one of the most strictly defined methods that provide good and reliable detection. And then the original image is blurred using Gaussian blur technique. The Gaussian blur is a type of image-blurring filter that uses a Gaussian function for calculating the transformation to apply to each pixel in the image. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. To get accurate information about pixel intensities Dual Tree Complex Wavelet Transform (DT-CWT) along with Median Filtering and interpolation are applied on original image and we get the modulated intensity image. The initial labels are obtained by performing K-means clustering on the Gray level pixel of intensities. The k-means result relies on the data set to satisfy the assumptions made by the clustering algorithms. It works well on some data sets, while failing on others. K=2 is more appropriate for our data set. The initial labels obtained by the k-means algorithm are not smooth enough, have morphological holes, and do not preserve the canny edges. The initial segmentation by K-means provides $X^{(0)}$ for the MAP algorithm, and the initial parameters $\theta^{(0)}$ for the EM algorithm. Therefore, to refine the labels HMRF-EM algorithm is applied. Along with binary edge map, blurred image and initial labels obtained from k-means, modulated intensity information is provided to the HMRF-EM algorithm.

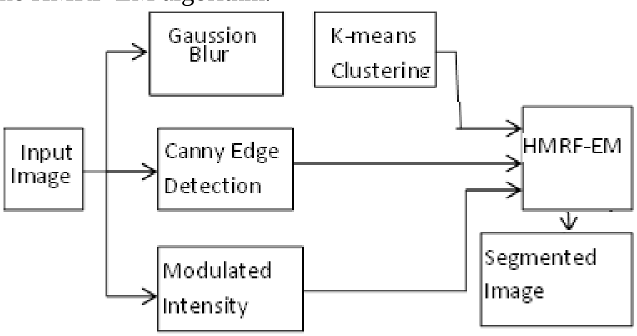

Figure 4.1: Proposed Methodology for Object Based Video Segmentation.

Steps for HMRF-EM algorithm is given below:

1. Start with initial parameter $\theta^{(0)}$.
2. Calculate the likelihood distribution $P^{(t)}(y_i|x_i,\theta_{x_i})$.
3. Using current parameter set $\theta^{(t)}$ to estimate the labels by MAP estimation:

$$x^{(t)} = \underset{x\,\in\,\chi}{argmax}\ \{P\ (y|x,\theta^{(t)})\ P(x)\}$$

subject to (1)

$$= \underset{x\,\in\,\chi}{argmin}\ \{U\ (y|x,\theta^{(t)}) + U(x)\}$$

4. Calculate the posterior distribution for all $l\ \epsilon$ L and all pixels y_i:

$$P^{(t)}(l|y_i) = \frac{G(y_i;\theta_l)P(l|x_{N_i}^{(t)})}{P^{(t)}(y_i)}\ (2)$$

Where $G(z;\ \theta_l)$ denote a Gaussian distribution function with parameters $\theta_l = (\theta_l = (\mu_l,\sigma_l))$:

$$G(z;\ \theta_l) = \frac{1}{\sqrt{2\Pi\,\sigma_l^2}}\exp\left(-\frac{(z-\mu_l)^2}{2\sigma_l^2}\right)\ (3)$$

and $x_{N_i}^{(t)}$ is the neighborhood configuration of $x_i^{(t)}$ and

$$P^{(t)}(y_i) = \sum_{l\,\in\,L} G(y_i;\ \theta_l)P(l|x_{N_i}^{(t)})\ (4)$$

Here $P(l|x_{N_i}^{(t)}) = \frac{1}{Z}\exp\ (-\sum_{j\in N_i} V_c(l,x_j^{(t)})\ (5)$

5. Use $P^{(t)}(l|y_i)$ to update the parameters:

$$\mu_l^{(t+1)} = \frac{\sum_i P^{(t)}(l|y_i)y_i}{\sum_i P^{(t)}(l|y_i)}\ (6)$$

$$(\sigma_l^{(t+1)})^2 = \frac{\sum_i P^{(t)}(l|y_i)(y_i-\mu_l^{(t+1)})^2}{\sum_i P^{(t)}(l|y_i)}\ (7)$$

In HMRF-EM we need to solve for x^* that minimizes the total posterior energy

$$x^* = \underset{x\,\in\,\chi}{argmin}\ \{U\ (y|x,\ \theta) + U(x)\}\ (8)$$

With given y and θ.

The likelihood energy is U (y|x, θ) is given as

$$U\ (y|x,\theta) = \sum_i U(y_i|x_i,\theta)$$

$$= \sum_i \left[\frac{(y_i-\mu_{x_i})^2}{2\sigma_{x_i}^2} + \ln\sigma_{x_i}\right].\ (9)$$

The prior energy function U (x) has the form

$$U\ (x) = \sum_{c\,\in\,C} V_c(x)\ (10)$$

Where $V_c(x)$ is the clique potential and C is the set of all possible cliques.

After applying the HMRF-EM we get the segmented image. Therefore, HMRF-EM refines the initial labels obtained from K-means.

5. Experimental Results

We calculated the PSNR and RMSE for the 12 different frames. The Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) are the two error metrics used to compare image compression quality.

$$MSE = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N}$$

Root Mean Square Error (RMSE) is square root of MSE hence it is calculated as follows

$$\text{RMSE}=\sqrt{\frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N}}$$

The RMSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The lower the value of MSE, the lower the error. The higher the PSNR, the better the quality of the image.

$$PSNR = 10\ log_{10}\left(\frac{R^2}{MSE}\right)$$

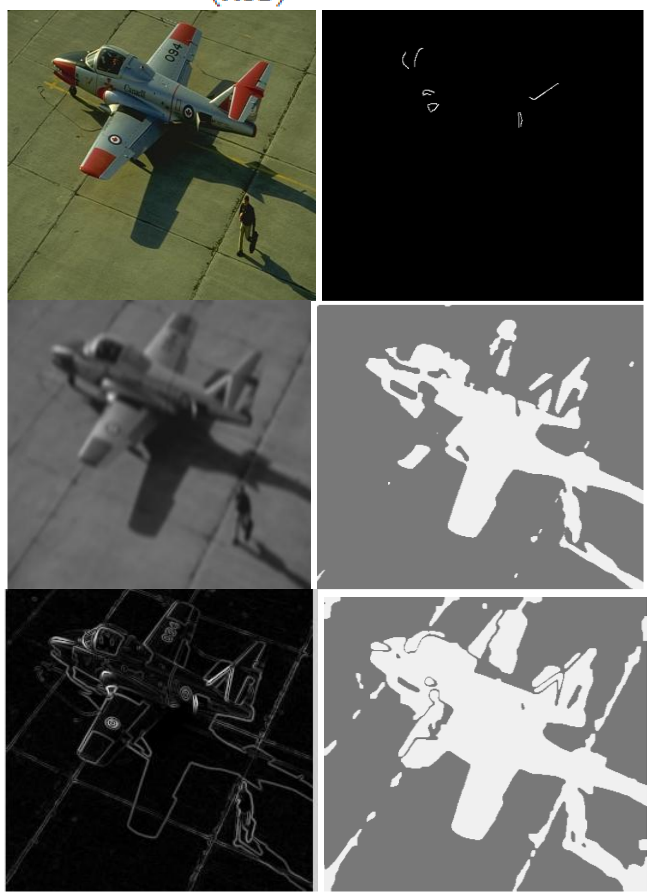

Figure 5.1: (a) Original Plane image (b) Canny edges (c) Gaussian blurred image (d) initial labels obtained by K-means (e) Modulated intensity (f) Segmented image using improved HMRF-EM algorithm (g) Total Posterior enery in each Iteration of improved HMRF-EM algorithm

The PSNR and RMSE of original image with segmented image using HMRF-EM algorithm and Improved HMRF-EM is calculated to show the segmentation quality Improvement as shown in table 5.1 and 5.2 resp.

Table 5.1: Showing RMSE of original image with segmented image and improved segmented image.

Input Image	Segmentation using HMRF-EM	Segmentation using Improved HMRF-EM
Plane	118.4722	104.7604
Temple	134.8722	30.6045
Beijing World Park 8	142.7049	142.7049

In this of RMSE is less in case of segmented images using improved HMRF-EM algorithm with original images. So, the improvement is shown by the less error. Sometimes the RMSE value of segmented image using HMRF-EM algorithm and segmented image using HMRF-EM is same for example, when we take Beijing WORLD Park 8 image as the Input image.

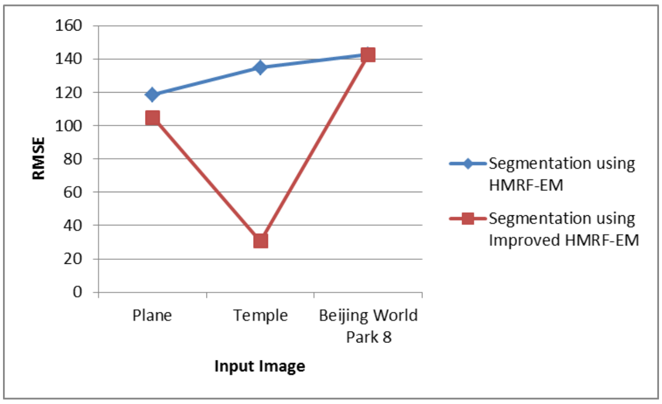

Figure 5.2 : Graph showing comparison of HMRF-EM and Improved HMRF-EM algorithm with reference to RMSE

Table 5.2: Showing PSNR of original image with segmented image and improved segmented image.

Input Image	Segmentation using HMRF-EM	Segmentation using improved HMRF-EM
Plane	6.6585	7.7269
Temple	5.5324	18.4151
Beijing World Park 8	5.0420	5.0420

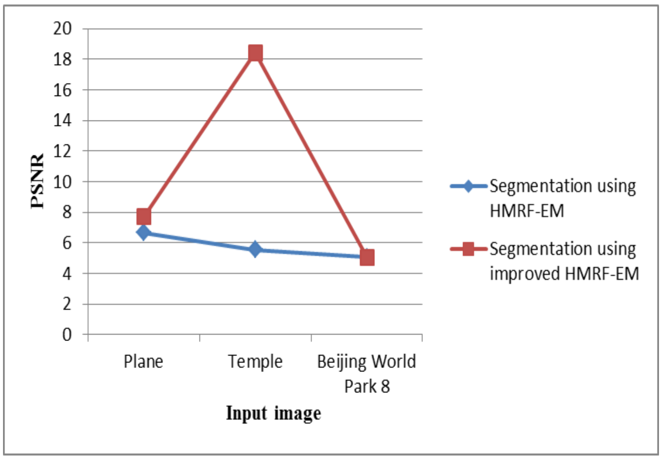

Figure 5.3 : Graph showing comparison of HMRF-EM and Improved HMRF-EM algorithm with reference to PSNR.

Thus the value of PSNR is more in case of image segmentation using improved HMRF-EM algorithm with original images. So, the improvement is shown by the improving segmented image quality.

6. Conclusion and Futur Scope

We proposed an Improved HMRF-EM algorithm that takes modulated intensity information along with edge map, Gray scale pixel of intensities and initial labels obtained from K-means. We applied Improved Hidden Markov Random field and its Expectation Maximization algorithm for unsupervised image segmentation. We have compared the results of segmentation by Improved Hidden Markov Random field and its Expectation Maximization (HMRF-EM) with the segmentation by Hidden Markov Random field and it's Expectation Maximization (HMRF-EM) and analysed that the segmentation quality improves with Improved Hidden Markov Random field and it's Expectation Maximization (HMRF-EM). In the future, the proposed work can give better segmentation results by using other advanced algorithm other than K-means to get initial labels and algorithm can be applied to segment more complex images. The proposed algorithm can also be applied for medical segmentation.

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