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An Experiment with Kernel Graph Cut and GMM Based Hidden Markov Random Field Image Segmentation Techniques

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Abstract: This paper discusses segmentation outcome of experiments conducted on Kernel Graph Cut and Gaussian Mixture Model based image segmentation techniques. The main objective of this experiment is to understand Effectiveness of these segmentation techniques on specific natural images having complex image composition. Effectiveness is assessed using human visual assessment and mathematical models such as Jaccard Index, Dice Coefficient and Hausdorrf Distance by comparing the segmented images with ground truth. While both techniques employ k-means as the clustering algorithm, this experiment findings suggest GMM based technique to be better over Kernel Graph Cut in terms of completeness and overall quality of segmentation.

Keywords: GMM, Hidden Markov Random Field, Expectation Maximization, Kernel Graph Cut, Automatic Image Segmentation, Effectiveness.

I. INTRODUCTION

In image segmentation, the intent is to partition image such that areas of interest or foreground are extracted for further processing. Gaussian Mixture Models (GMMs) are statistical methods and amongst the most mature methods for clustering though they are also used for density estimation A Gaussian Mixture Model is a probabilistic model that can be used to represent normally distributed subpopulations within an overall population and sometimes establishes the form of unsupervised learning. GMMs assumes that all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. Expectation-Maximization (EM) algorithm or Maximum A Posteriori (MAP) estimation is usually employed to estimate GMM parameters from a well-trained prior model.

In image modelling, wherein, a set of 2-D images are subjected to modelling techniques to project different 3-D views as suitable to the task at hand, Markov Random Fields (MRFs) have been found to be very flexible for stereo matching (voice matching), image segmentation, image and texture synthesis, image compression and restoration, surface reconstruction, image registration, super-resolution, information retrieval, etc. Hidden Markov Random Field model is derived from Hidden Markov Models which have basis of 1D Markov Chains. Due to its 1D design, these cannot be directly applied to solve 2D/3D problems in image or volume segmentation. A Hidden Markov Random Field (HMRF) is a special case of HMM having an underlying Markov Random Field instead of Markov chain and hence not limited to 1D.

As explained in [1], MRFs have been quite widely used for computer vision problems, such as image segmentation [2], surface reconstruction [3] and depth inference [4]. These are quite successful due to the efficient algorithms, such as Iterated Conditional Modes [5], and its consideration of both “data faithfulness” and “model smoothness” [6]. The HMRF-EM framework was first proposed for segmentation of brain MR images [7]. It is quite possible that in certain domain specific dataset, intensity distribution of foreground and background might be consistent, thus allowing us to learn the parameters by manually labelling some images and use these parameters to segment other images using MRF. Unlike in MRF, in HMRF methods, as there are no training stages and since prior knowledge is not known regarding foreground and background intensity distribution, the best fit is to use an Expectation Maximization algorithm to learn the parameter set and label configuration.

As elaborated in [8, 9], Expectation Maximization (EM) is an iterative method to find the maximum likelihood or maximum a posteriori (MAP) estimates of parameters in statistical models, where the model may have hidden variables. The EM algorithm performs an expectation step (E), which creates a function, for the expectation of the log-likelihood and evaluates it using the

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current estimate for the parameters. This step is followed by a maximization step (M), which computes parameters maximizing the expected log-likelihood found during the E step. These parameter-estimates are then used to determine the distribution of the hidden variables in the next E step. These two processes alternate until there is no change.

Kernel Graph Cut as explained in detail in [10], examine if kernel mapping of image data can influence more general multi-region segmentation of images using unsupervised graph cut formulation than Gaussian. The kernel function maps image data implicitly into data of higher dimension, due to which unsupervised graph cut formulation of the piecewise constant model becomes applicable. Without explicit evaluation of the transform, the Euclidean norm of the dot product in the in the higher dimensional space of the transformed data can be expressed via the kernel function making mapping an implicit one.

The proposed method has two steps. In step 1, from the piecewise constant model, evaluation of the deviation of the mapped image data within each region performed by kernel induced term. Step 2 has function of the region indices forming the regularization term. Proposed functional minimization is achieved by iterations of the two successive steps using a common kernel function, in step 1, computational benefits of graph cuts [11, 12] with respect to image segmentation causing functional minimization and fixed point computation evaluation leading to minimization of regions parameters.

II. ACCURACY MEASURES

In this experiment, similar to [13] segmented images were compared with ground truth to assess the accuracy of both the segmentation techniques. Segmented images were compared with the ground truth images to assess by computing Jaccard Index, Dice Coefficient & Hausdorff Distance

A. Jaccard Index

The Jaccard Index [14], also known as the Jaccard similarity coefficient, is a statistic used for comparing the similarity and diversity between the two sets. The Jaccard coefficient measures similarity between finite sample sets, and is defined as the size of the intersection divided by the size of the union of the sample sets:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

Eq. (1)

The Jaccard distance is obtained by subtracting the Jaccard coefficient from 1 and indicates dissimilarity between two sets. It is complementary to the Jaccard coefficient and is expressed by dividing the difference of the sizes of the union and the intersection of two sets by the size of the union:

$$d_J(A,B) = 1 - J(A,B) = \frac{|A \cup B| - |A \cap B|}{|A \cup B|}$$

Eq. (2)

B. Dice Coefficient

The Sørensen–Dice index [15], which is independently developed by the botanists Thorvald Sørensen and Lee Raymond Dice, is also an indicator used for comparing the similarity of two sets. Sorensen's formula was intended to be applied to presence/absence data, and is –

$$QS = \frac{2|A \cap B|}{|A| + |B|}$$

Eq. (3)

Where, |*A*| and |B| are the numbers of species in the two samples. QS is the quotient of similarity and ranges between 0 and 1. It can be viewed as a similarity measure over sets.

C. Hausdorrf Distance

The Hausdorrf distance [16], is also known as Hausdorrf metric, and it measures how far two subsets of a metric space are from each other. Hausdorrf distance is the greatest of all the distances from a point in one set to the closest point in the other set. Let X and Y be two non-empty subsets of a metric space (M, d). We define their Hausdorrf distance d H(X, Y) as –

$$d_H(X,Y) = \inf \{\epsilon \geq 0;\ X \subseteq Y_\epsilon \text{ and } Y \subseteq X_\epsilon\}$$

Eq. (4)

Where,

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$$X_\epsilon \bigcup_{x \in X} \{z \in M ; d(z,x) \leq \epsilon$$

q. (5)

III. THE EXPERIMENT

Similar to [13], in this experiment also, we have studied GMM Based Hidden Markov Random Field [1] and Kernel Graph Cut [17] techniques and performed experiments using MATLAB, to understand and study effectiveness of these techniques and accuracy of segmentation by assessing –

A. Visual confirmation
B. Jaccard Index
C. Dice Index
D. Hausdorrf Distance

The experiment involved performing segmentation, using varying values for number of clusters for k-means clustering algorithm, GMM mixtures, smoothness factor and beta, study the impact on the output and such combination was chosen which had resulted in best output for final segmented image. For this experiment, select images from Single Object Image Segmentation Dataset of natural images [18] has been used. This dataset is made freely available for research purposes, by Department of Computer Science and Applied Mathematics, Weizmann Institute of Science. This image dataset provides source image as well as ground truth for comparison. As stated in [18], Ground Truth has been constructed using manual segmentation by human subjects. We have used RGB images as an input to the segmentation process.
Following process was followed in this experimental study.

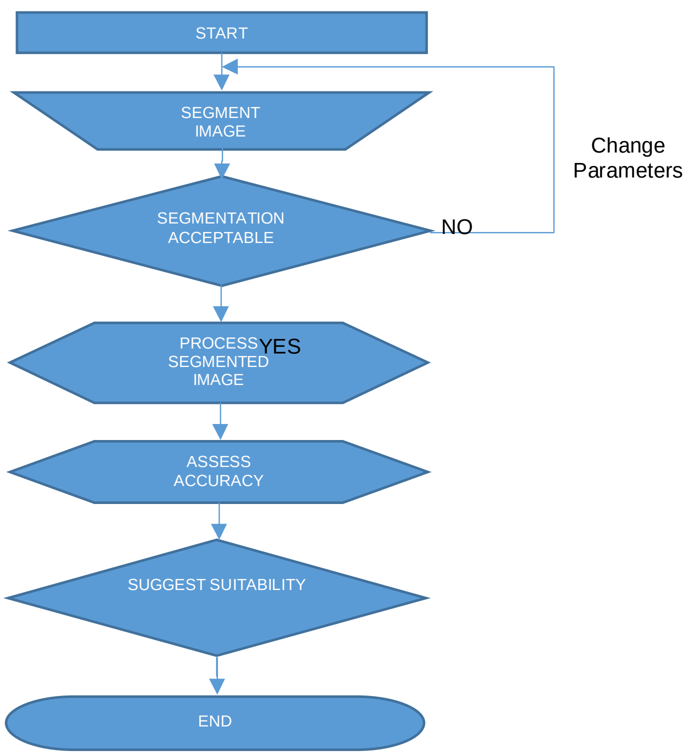

Figure (1)

IV. OBSERVATIONS

In this experiment we have performed segmentation using GMM-HMRF and Kernel Graph Cut techniques. Experiment was conducted on various images, however, we have referred only 5 images which we considered to be complex to pose a challenge to the technique with the intent to assess its suitability. All the images were RGB images. Let us first look at the GMM-HMRF

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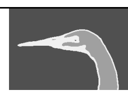
findings. The images have been resized to fit this document. The experiment was conducted using Matlab version 2011a on Windows PC. It was observed that GMM is computationally expensive and more the GMM components, longer it took for the segmentation to occur, largely due to needed iterations which must converge for successful segmentation. This experimental code for GMM-HMRF uses k-means as clustering technique combined with Expectation Maximization algorithm for the Gaussian based Hidden Markov Random Field. Various values for number of k-clusters and smoothness term were used, however, only the best output is selected for this study.

Segmentation Set I			
Original Image	Initial Labels	Final Labels	Final Image (Human Intervention)
			
Jaccard Index = 0.7933			
Dice Coefficient = 0.8848			
Hausdorrf Distance=2.6458			

Segmentation Set II			
Original Image	Initial Labels	Final Labels	Final Image (Human Intervention)
			
Jaccard Index = 0.8583			
Dice Coefficient = 0.9237			
Hausdorrf Distance=5.1962			

Segmentation Set III			
Original Image	Initial Labels	Final Labels	Final Image (Human Intervention)
			
Jaccard Index = 0.9454			
Dice Coefficient = 0.9719			
Hausdorrf Distance=1.7321			

Segmentation Set IV			
Original Image	Initial Labels	Final Labels	Final Image (Human Intervention)
			
Jaccard Index = 0.9757			
Dice Coefficient = 0.9877			
Hausdorrf Distance=4.6904			

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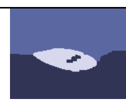
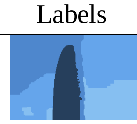
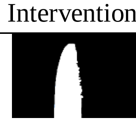
Segmentation Set 5			
Original Image	Initial Labels	Final Labels	Final Image (Human Intervention)
			
Jaccard Index = 0.9300			
Dice Coefficient = 0.9638			
Hausdorrf Distance= 3.1623			

As is evident from the output of the segmentation process, which is a labelled image (Final Labels), we find that this technique has been able to identify the foreground quite well, however, in some images there are additional areas also, which are part of background appearing in the final output. Understanding of the object to be extracted, is needed to successfully extract the foreground from the background. GMM-HMRF was found to be computationally expensive as well. Also, it was noticed that although images appear to be successful visually, when these were subjected to statistical methods to ascertain accuracy of the segmentation, the accuracy was found to be quite low for segmentation set 1 & 2. GMM-HMRF falls under the category of automatic segmentation technique and is not sufficient alone to get us the desired image for further use in the applications.
Let us now review the output of Kernel Graph Cut segmentation technique.

Segmentation Set VI			
Original Image	Regions	Final Labels	Final Image (Human Intervention)
			
Jaccard Index = 0.9039			
Dice Coefficient = 0.9495			
Hausdorrf Distance=3.7417			

Segmentation Set VII			
Original Image	Regions	Final Labels	Final Image (Human Intervention)
			
Jaccard Index = 0.9712			
Dice Coefficient = 0.9854			
Hausdorrf Distance=5.6569			

Segmentation Set VIII			
Original Image	Regions	Final Labels	Final Image (Human Intervention)
			
Jaccard Index =0.7321			
Dice Coefficient = 0.8453			
Hausdorrf Distance=4.8990			

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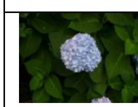
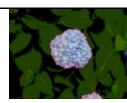
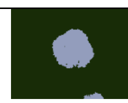
Segmentation Set IX			
Original Image	Regions	Final Labels	Final Image (Human Intervention)
			
Jaccard Index = 0.9728			
Dice Coefficient = 0.9862			
Hausdorrf Distance=4.7958			

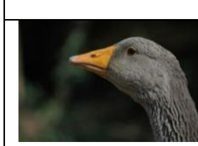
Segmentation Set X			
Original Image	Regions	Final Labels	Final Image (Human Intervention)
			
Jaccard Index = 0.9752			
Dice Coefficient = 0.9874			
Hausdorrf Distance=2.8284			

We found Kernel Graph Cut to be computationally quite faster as the algorithm makes just one pass through the image. Similar to GMM-HMRF method, we performed experiment using various values for k-means cluster as well as smoothness term and have selected the best output from the multiple segmentation runs. Output of the Kernel Graph Cut was not found to be suitable for direct use. We had to remove unneeded background information to be able to perform accuracy checks. As can be seen from the above segmentation sets, barring segmentation set 8 which has resulted in failed segmentation, this technique has done a good job as well, however, user intervention in the form of post processing is needed for segmented image to be usable further in target applications.

For both segmentation techniques, the output images were converted into binary form before subjecting those to accuracy measure. Manually, knowing the object, intuitively, we had to remove non-needed information and for the same, GIMP [19] toolkit was used. The accuracy measures were calculated for these final images by comparing it against the Ground Truth [18].

Let us now review failed segmentation sets for both these techniques. Below images are quite complex in terms of similarity in foreground and background, low intensity in few areas, etc.

A. Failed Segmentation Sets – GMM-HMRF

Segmentation Set XI	
Original Image	Segmented Image
	

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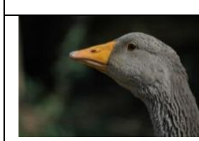
Segmentation Set XII	
Original Image	Segmented Image
	

Segmentation Set XIII	
Original Image	Segmented Image
	

B. *Failed Segmentation Sets – Kernel Graph Cut*

Segmentation Set XIV		
Original Image	Regions	Segmented Image
		

Segmentation Set XV		
Original Image	Regions	Segmented Image
		

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Segmentation Set XVI		
Original Image	Regions	Segmented Image
		

As it is evident from this experiment, both the techniques have failed to successfully segment these complex images.

V. DISCUSSION

Both the techniques fall under category of automatic segmentation techniques and have been quite effective in segmenting these complex images. Both techniques have resulted in an output image which requires post processing before further subjecting to applications. GMM-HMRF was found to be computationally quite expensive due to iterative nature whereas Kernel Graph Cut, which is based on [20, 21, 22, 23 and 24] makes a single pass through the image and is quite faster. GMM-HMRF was found to be largely successful on all the images whereas, Kernel Graph Cut could not successfully segment one particular image belonging to segmentation set 8. Kernel Graph Cut on the other hand has resulted in sharper object boundary, particularly noticeable in image segmentation set 10 as compared with segmentation set 5 of GMM-HMRF. There are actually three foreground objects in these segmentation sets, out of which one is complete and others are partial. The foreground object in these sets has lots of edges and those have come out very well using Kernel Graph Cut. Interestingly, in this same segmentation sets (5 and 10), we find that GMM-HMRF could identify foreground objects (completeness) much better than Kernel Graph Cut as is evident from the output image (final labels).

VI. CONCLUSION

Both segmentation techniques have been largely successful in segmenting these complex images. However, we find Kernel Graph Cut has yielded sharper image boundary, whereas GMM-HMRF seems to perform better on completeness. Both require post processing for segmented images to be useful in further applications. Relatively, accuracy was found to be marginally better in Kernel Graph Cut technique. Both techniques are found to be effective on moderately complex images only.

VII. ACKNOWLEDGMENT

We acknowledge the great work done by the authors of GMM-HMRF and Kernel Graph Cut automatic image segmentation techniques. Both these techniques are immensely effective and useful for fellow researchers to study various aspects of image segmentation.

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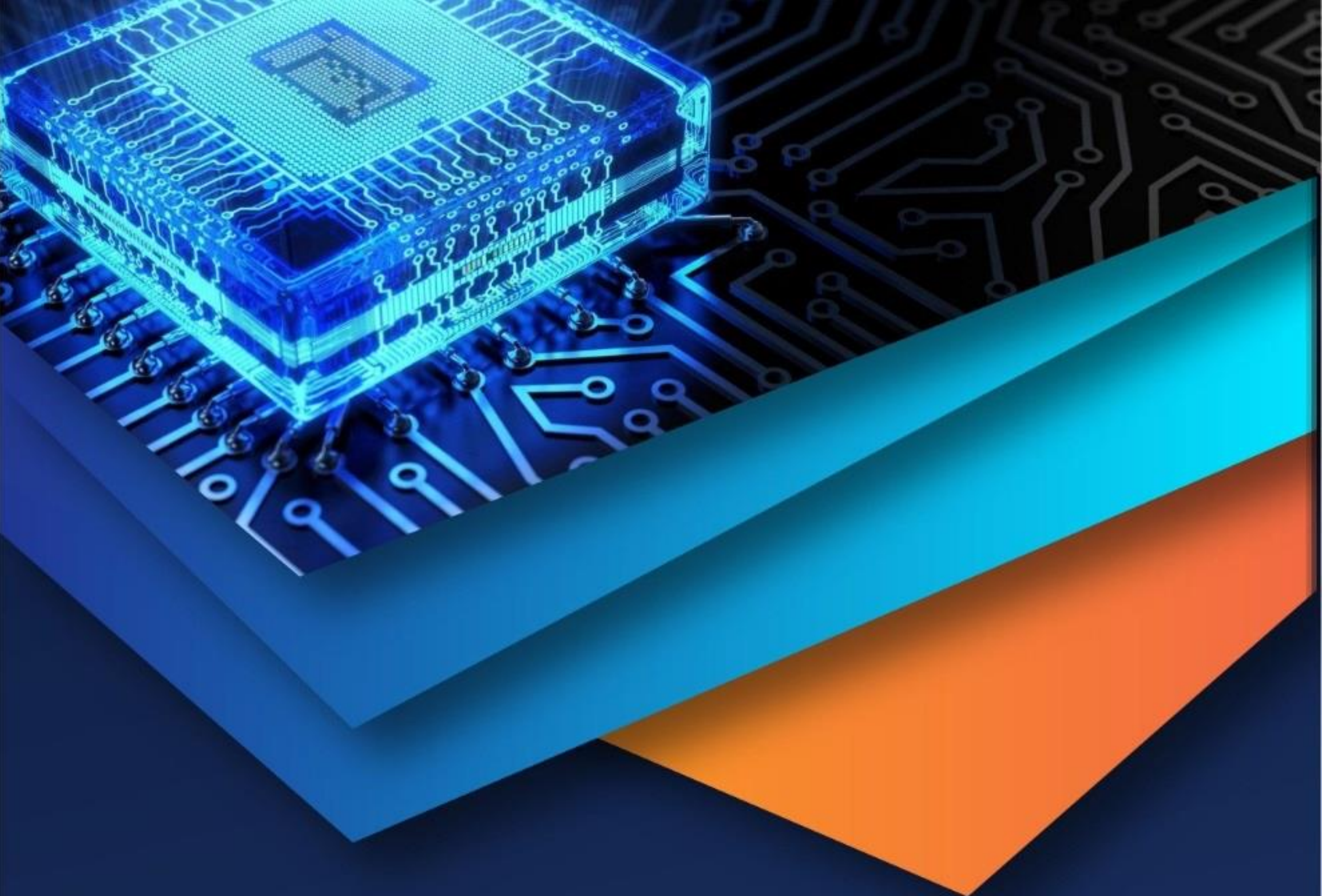

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