Abstract-- We propose a Probabilistic Graph based Model for interactive image segmentation. A multilayer probabilistic Graph is constructed from an oversegmentation of the image to model the relationships among super pixel regions, edge segments and vertices. We used an iterative procedure to merge several regions based on the probability of the regions. Regions are merged until the user is satisfied with the segmentation. Each node’s probability is updated after each iteration. With the help of proper user intervention the input image is segmented in short time period. We evaluate the proposed model on many images in the database. The results demonstrate that the Graphical model can be used for interactive image segmentation (IS). The results also shows that the proposed method has good accuracy and efficiency for both segmenting the image and extraction of the object from the segmented image.

Index Terms- Graphical Model, interactive image segmentation (IS), image segmentation, region merging.

I. INTRODUCTION

Image segmentation is an important subject in the field of image processing and computer vision. It still remains as a challenge when the image involves complex natural scenes. Great efforts have been made to develop more advanced techniques in recent years. The process of partitioning a digital image into multiple regions or sets of homogeneous pixels is called image segmentation. Actually, partitions are different objects in image which have the same texture or colour. 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. All the pixels in a region are similar with respect to some characteristics or computed property, such as colour, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. This technique has a variety of applications including computer vision, image analysis, medical image processing, remote sensing and geographical information system. Image segmentation is based on two basic properties, first intensity values involving discontinuity that means sudden or abrupt changes in intensity as edges and second similarity that means partitioning a digital image into regions according to some pre-defined likeness criterion. Many approaches have been proposed earlier which includes region growing [1], normalized cuts [2], clustering [3], grab-cut method [4], active contours [5], and MRF (Markov Random Field) based approaches [6] etc. All these approaches are data driven approaches.

The data driven approaches may not produce satisfactory results in segmentation when there are shadow, low contrast areas, occlusion, cluttering and noise present in the image. When these things are present in the image than prior knowledge is very necessary for segmenting the given image for producing satisfactory results. These methods incorporate the prior information in a deterministic manner, ignoring various uncertainties associated in the image segmentation process and making very difficult to take user’s intervention into the segmentation process. There are two basic types of graphical models: the undirected graphical model and the directed acyclic graphical model. The undirected graphical model can represent noncasual relationships among the random variables [7]. MRF models have been widely used for image segmentation. They incorporate the spatial relationships among neighbouring labels as a Markovian prior. This prior can encourage the adjacent pixels to be classified into the same group. As an extension to MRFs, the Conditional Random Field (CRF) [8] is another type of undirected graphical model that has become increasingly popular. While both MRF and CRF models can effectively capture noncasual relationships they cannot model the directed relationships. This problem can be solved by another type of graphical model, i.e., the directed acyclic graphical model such as Bayesian Network (BN) [9][10].

The automatic segmentation approaches may also fail even though they use prior information in segmentation process. The main reason behind this is the complexity of segmentation of image in real applications. The complexity is due to the several reasons like shadow, low contrast areas, occlusion, cluttering and noise in the image. These reasons make the segmentation process quite difficult and challenging. The use of interactive image segmentation process is the solutions of such problems. In the interactive image segmentation the proper user’s intervention is required for segmentation process. Because user gives the clue for segmenting the image in the process the results are more improved and satisfactory. We develop a graphical model for segmentation that can incorporate various probabilistic relationships and apply it to the segmentation problem. Our model captures the natural causal relationships among three entities in image segmentation: regions, edges, and vertices (i.e., the junctions).

There are many works on interactive image segmentation [4],[11], [12, 13, 14]. They demonstrate the usefulness of the user’s intervention for improving segmentation.
II. RELATED WORK

Eric N. Mortensen and Jin Jia [15] proposed a BN model with two layers for image segmentation, which captures the relationships between edge segments and their vertices. Given a user input seed path, they use minimum path spanning tree (MPST) graph search to find the most likely object boundaries. They also encode statistical similarity measure between the adjacent regions of an edge into its a priori probability therefore implicitly integrating region information.

In the early study [16] they use the similar BN model for both automatic and interactive segmentation. Their approach can find multiple non-overlapping closed contours before any given user’s intervention. The intervention will serve as an evidence to help select a single closed contour that covers the object of interest.

Lei Zhang, Zhi Zeng, and Qiang Ji [17] proposed a method to extend the Chain Graph (CG) model. CG is a hybrid Probabilistic Graphical Model (PGM) which contains both directed and undirected links. Its representation is powerful enough to capture heterogeneous relationships among image entities. For CG they first oversegment the image into superpixels and find out different heterogeneous relationships among image entities (superpixels, vertices or junctions, edges, regions etc.) They construct the CG model with parameterized links with derived Joint Probability Distribution (JPD). These links are represented by either potential function or conditional probabilities. They first create a Directed Master Graph then create undirected sub-graphs for some terms in the JPD of Directed Master Graph. They segment the image into two parts foreground and background. In the end they apply probabilistic inference in the foreground to find out most probable explanation.

Kittipat Kampa, Duangmanee Putthividhya and Jose C. Principe [18] design a probabilistic unsupervised method called Irregular Tree Structure Bayesian Network (ITSBN). The ITSBN is constructed according to the similarity of image regions in an input image. ITSBN is a Directed acyclic graph (DAG) with two disjoint sets of random variables hidden and observed. The original image is oversegmented in multiscale hierarchical manner then they extract features from the input image corresponding to each superpixel. According to these superpixels ITSBN is built for each level. After applying the learning and inference algorithms the segmented image is produced.

Fei Liu, Dongxiang Xu, Chun Yuan and William Kerwin [19] combined the BN (Bayesian Network) and MRF (Markov Random Field) to form an image segmentation approach. The BN generates a probability map for each pixel in the image and then MRF prior is incorporated to produce the segmentation. It is an interactive image segmentation method. First each pixel will be individually assigned a probability value to be each given class. According to such probability map, BN provides a mechanism to convert the problem from feature space to image domain and they consider the prior knowledge on the image model and the spatial relationships between pixels, they use MRF based model to produce the segmentation results.

Costas Panagiotakis, Ilias Grinias, and Georgios Tziritas [20] proposed a framework for image segmentation which uses feature extraction and clustering in the feature space followed by flooding and region merging techniques in the spatial domain, based on the computed features of classes. They use a new block-based unsupervised clustering method which ensures spatial coherence using an efficient hierarchical tree equipartition algorithm. They divide the image into different different blocks based on the feature description computation. The image is partitioned using minimum spanning tree relationship and mallows distance. Then they apply K-centroid clustering algorithm and Bhattacharya distance and compute the posterior distributions and distances and perform initial labelling. Priority multiclass flooding algorithm is applied and in the end regions are merged so that segmentation results are produced.

III. PROPOSED FRAMEWORK

For interactive image segmentation, we need a model that can conveniently take the user’s intervention and according to the user intervention it produces the segmentation result. We propose a Graphical Model based on the regions (superpixels), edges, vertices (junctions) and the relationships between these image entities for interactive image segmentation.

We start from the top left corner of the image and take the first pixel from each region. The pixel represents that whole region. Now we find out the connectivity of regions to each other. We take the first pixel and check for the connected regions and the first pixels of those regions. Now we connect all the pixels to each other.

The flowchart of the proposed algorithm is given below. Given the edge map of an oversegmented image, we construct a graphical model (GM) to capture the relationships between regions, edge segments and vertices. Each pixel has the label that represents the region number to which the pixel belongs. The label graph is constructed when all the pixels are connected to each other.
Here we calculate the probability of each region for merging with the other regions on the basis of colour histogram. We use an iterative and interactive approach for the segmentation of the image. User start the process and the model starts merging the regions, at the same time graph is generated to show the connectivity of the regions and the probability of regions to merging with the other regions.

After first iteration some regions that are most probable merged with each other and results a new graph with less regions and fewer pixels and connectivity. Probability is calculated for each iteration. The calculated probability is the probability of the pixel to merge with other pixels in the graph. This process continues until the user is satisfied or there are no region remains in the image. Once the user is satisfied it can stop the process.

The final segmentation result is obtained by the user intervention. The user can also interact with the final segmented image to extract the object of interest from the image.

IV. IMAGE SEGMENTATION FRAMEWORK

4.1 Constructing Superpixels

We use the Graphical Model as the basic framework for image segmentation. We construct the Graphical model from an oversegmentation of the image. The edge map in the oversegmentation consists of superpixel regions.

If I is set of all image pixels, then by applying segmentation we get different unique regions like \{ R_1, R_2, R_3, ..., R_n \} which when combined formed ‘I’. Basic formulation is as follows:

(a) \( \bigcup_{i=1}^{n} R_i = I \) where \( R_i \cap R_j = \emptyset \)

(b) \( R_i \) is a connected region, \( i=1, 2, ..., n \).

(c) \( P(R_i) = \) TRUE for \( i=1, 2, ..., n \).

(d) \( P(R_i \cup R_j) = \) FALSE for \( i \neq j \).

Where \( P(R_i) \) is a logical predicate defined over the points in set \( R_i \).

Condition (a) indicates that segmentation must be complete; every pixel in the image must be covered by segmented regions. Segmented regions must be disjoint. Condition (b) requires that points in a region be connected in some predefined sense like 4-neighbourhood or 8-neighbourhood connectivity. Condition (c) deals, the properties must be satisfied by the pixels in a segmented region e.g. \( P(R_i) = \) TRUE if all pixels in \( R_i \) have the same gray level. Last condition (d) indicates that adjacent regions \( R_i \) and \( R_j \) are different in the sense of predicate \( P \).
4.2 Graph Construction

We construct the graph corresponding to the segmented image which represents the relationship between the different image regions. An edge in the graph shows the connectivity of the regions to each other. Here $R_1$, $R_2$, $R_3$, $R_4$, $R_5$ and $R_6$ are the regions in the segmented image and $P_1$, $P_2$, $P_3$, $P_4$, $P_5$ and $P_6$ are the corresponding probabilities.

Region $R_1$ is connected to $R_2$ and $R_3$, $R_2$ is connected to $R_4$ and $R_5$, $R_3$ is connected to $R_4$ and $R_6$ and $R_4$ and $R_5$ are connected to each other. The probability corresponding to the region is the probability of merging with the other smaller regions.

4.3 Probability Calculation

Let $V = \{R_1, \ldots, R_n\}$ be a set of all regions and $P(V)$ denote the joint probability distribution over $V$.

Using the Fundamental Rule, $P(V)$ can be written as

$$P(V) = \prod_{i=1}^{n} P(R_i | R_1, \ldots, R_{i-1}, R_{i+1}, \ldots, R_n)$$

Thus, any region can be represented as a product of conditionals, e.g., $P(R_1, R_2, R_3) = P(R_3 | R_1, R_2) P(R_2 | R_1) P(R_1) = P(R_3 | R_1, R_2) P(R_2 | R_1) P(R_1)$

4.4 Region Merging

We have many small regions available in the edge map. A region can be described in many aspects, such as the colour, edge [23], texture [24], shape and size of the region. Among them the colour histogram is an effective descriptor to represent the object colour feature statistics and it is widely used in pattern recognition [25] and object tracking [26] etc. Colour histogram is more robust than the other feature descriptors. This is because the initially segmented small regions of the desired object often vary a lot in size and shape, while the colours of different regions from the same object will have high similarity. Therefore, we use the colour histogram to represent each region. The RGB colour space is used to compute the colour histogram. We uniformly quantize each colour channel into 16 levels and then the histogram of each region is calculated in the feature space of $16 \times 16 \times 16 = 4096$ bins.

4.5 Constructing Mask

Once the regions are merged and the image with desired segments are generated we construct the mask of the image for extracting object of interest from it. For constructing the mask of the segmented image we convert it into the gray scale image. In the segmented gray scale image we assign value 255 to the pixels at the boundaries and 0 to the rest of the pixels in the image. This constructs the mask of the image.
4.6 Binarization Of Object Contour

Once the regions are merged and the image with desired segments are generated we construct the mask of the image for extracting object of interest from it. For constructing the mask of the segmented image we convert it into the gray scale image.

4.6 Object Extraction

For extraction of object of interest from the segmented image we use the mask and Boundary Fill algorithm. The object extraction from the image is also interactive. The user clicks on the desired region in the image. On the basis of the user click and the mask of the image the region’s pixel’s value set to the colour value in the image and the rest of the part of the image pixel’s values are set to 0.

V. RESULT AND ANALYSIS

In order to examine this algorithm, the experimental results were under the software environment of Matlab 7.5. We tested the proposed model on several images in the database. The database includes many images of birds, horses and aeroplanes that have different appearances and poses and background includes more different kinds of scenes, which makes it challenging to segment these images. All of the images are first oversegmented using the mean shift method [28]. After the oversegmentation of image we construct the graph and find the probability. Then we perform similarity region merging to merge the regions on the basis of colour.
The model performs region-merging based on the colour histogram of the image. After region merging the new graph is constructed and new probability is calculated for each node in the graph. Maximum probability of a node shows that the region will be merged to other smaller regions present in the image and results in a bigger region. It is an iterative procedure and number of iterations depends on the user satisfaction. Finally, we want to point out that the application of the graphical model is not limited to image segmentation. It can find applications in many different computer vision problems including object tracking, object recognition etc. Our experimental results demonstrate the promising capability of the proposed Graphical model for effective interactive image segmentation.

REFERENCES


