

Improved BN Model for Regular and Interactive Image Segmentation

¹Y. Siva Prasad, ²K. V. Srinivasa Rao

^{1,2}Dept. of CSE, Prakasam Engineering College, Kandukur, AP, India

Abstract

We propose a new enhanced Bayesian network (BN) model for both automatic and interactive image segmentation. A multilayer BN is constructed from an over segmentation to model the statistical dependencies among superpixel regions, edge segments, vertices, and their measurements. The BN also incorporates various local constraints to further restrain the relationships among these image entities. The proposed system construct structures for the background and foreground images, i.e. two phase image constructor, and clusters the structured grouped pixels by performing the BN model for easy image segmentation. Given the BN model and various image measurements, belief propagation is performed to update the probability of each node. Image segmentation is generated by the most probable explanation inference of the true states of both region and edge nodes from the updated BN. Besides the automatic image segmentation, the proposed model can also be used for interactive image segmentation. While existing interactive segmentation (IS) approaches often passively depend on the user to provide exact intervention, we propose a new active input selection approach to provide suggestions for the user's intervention. Such intervention can be conveniently incorporated into the BN model to perform actively IS. We evaluate the proposed model on both the Weizmann dataset and VOC2006 cow images. The results demonstrate that the BN model can be used for automatic segmentation, and more importantly, for actively IS. The experiments also show that the IS with active input selection can improve both the overall segmentation accuracy and efficiency over the IS with passive intervention

Keywords

Active Labeling, Bayesian Network (BN), Image Segmentation, Interactive Image Segmentation

I. Introduction

Image segmentation is a difficult problem in computer vision. It aims at partitioning an image into constituent regions of interest. Many approaches have been proposed before, including the clustering method [1], region growing [2], active contours [3], normalized cuts [4], graph-cut-based approaches [5], Markov random fields (MRFs) [6], etc. These methods are basically data-driven approaches. The data-driven method sometimes fails to produce satisfactory segmentation when there are shadow, occlusion, cluttering, low contrast area, or noise in the image. Incorporation of contextual and prior information is very important to improve segmentation under such situations.

Researchers have therefore incorporated global shape information, local image constraints such as smoothness, and other domain knowledge for image segmentation. Some previous works have already tried to incorporate certain prior knowledge into image segmentation[a]. By incorporating the prior knowledge, these approaches successfully improve segmentation in cases, where the purely data-driven methods may fail. In addition, the MRF-based approach is often used to capture certain prior knowledge. It can encode the local spatial relationship among random variables.

However, MRF is not effective in capturing the global spatial relationship or long-range interaction. An additional hidden layer is normally added to model such relationships [10], which makes the MRF model more complex and computationally inefficient. More importantly, these existing IS an approach often solely depend on the user to passively select the next intervention. However, the user may not easily know which intervention is most effective and should be performed first. In interactive labeling domain, researchers have studied the active learning approach for helping the user select the label to be first corrected [14-17].

The active learning proceeds sequentially, with the learning algorithm actively asking for the labels of some instances from a user. The objective is to ask the user to label the most informative instance in order to reduce the total labeling cost and to accelerate the learning process. Similar strategies can be incorporated into the interactive labeling domain to form a new active labeling approach. For active labeling, the key is the sample selection strategy, which selects the next sample for the user to label based on a predefined criterion. A better sample selection criterion should simultaneously maximize the performance while minimizing the amount of human intervention. For classification problems, the most commonly used active learning criterion is the close-to-boundary criterion [18]. Other criteria have also been proposed. For example[a].

In this paper, we aim at finding the object boundary from the edge map of an oversegmented image. We propose a new enhanced Bayesian Network (BN) [19-20] to model this segmentation problem in a probabilistic way. Specifically, a multilayer structured BN is constructed to model regions, edge segments, vertices, their measurements, and their causal relationships. The BN also captures some local constraints to restrain the relationships among image entities. Given the BN, image segmentation is performed through a probabilistic inference. the modeling power of BN, it is very easy to incorporate new constraints and measurements into the model.

The human intervention can be easily added into the model as new evidence in an incremental, interactive, and sparing manner. This characteristic makes the proposed BN model very suitable for interactive image segmentation. In addition, we propose a new active input selection process to automatically generate a ranked list of candidates for the user to choose as the user's next intervention. This process can effectively reduce the total user's involvement for performance improvement. The impacts of newly input evidence are systematically propagated through the entire BN via belief propagation.

In this way, constrained segmentation can be done in an incremental and interactive manner, fully utilizing the previous segmentation results.

II. Related Work

BN is a powerful probabilistic graphical model that has been applied in computer vision. Early in 1990s, Sarkar and Boyer [21] applied BN to group low-level edge segments for high-level image understanding. Westling and Davis [22] applied BN for the interpretation of complex scenes. Feng et al. [23] combined BN

with neural network for scene segmentation. A trained neural network provides the local predictions for the class labels.

These predications are then fused with the BN prior model for scene segmentation. Liu et al. [24] combine BN and MRF to form an image segmentation approach. The BN generates a probability map for all pixels. An MRF prior is further incorporated to produce the segmentation. Mortensen and Jia [25] used a two-layer BN model for image segmentation, which captures the relationships between edge segments and their junctions.

Given a user-input seed path, they use the minimum-path spanning tree graph search to find the most likely object boundaries. Other than imposing a simple contour closure constraint, their method is basically a data-driven approach. They use the intensity gradient and local curvature as the edge's measurement. In addition, they encode a statistical similarity measure between the adjacent regions of an edge into its a priori probability, therefore, implicitly integrating region information. In their early study [26], they used a similar BN model for both automatic and IS. Their approach can find multiple nonoverlapping closed contours before any user's intervention is given. The user's input will serve as evidence to help select a single closed contour that encompasses the object of interest. Although these researchers have successfully applied BN in their specific problems, most of them only use a simple BN structure (typically a naïve BN). For complex problems, this model may not be expressive enough to model many different kinds of image entities and their relationships. How to effectively capture these relationships using a BN is crucial to solve these difficult problems.

In our latest study on automatic image segmentation, we introduce a unified graphical model combining the directed graphical model with the undirected graphical model. It allows capturing more complex and heterogeneous relationships among image entities. Compared with the BN model proposed in this paper, the unified graphical model is more expressive and more powerful. But the unified model was only used for automatic segmentation. In contrast, this paper focuses on interactive image segmentation with the human in the loop.

This paper also integrates an active learning approach into the interactive image segmentation, which is new in this domain. Other than automatic image segmentation, several semi-automatic segmentation approaches have been proposed before. Intelligent scissors [13] allow the user to give seeds to guide the segmentation algorithm to find the low-cost path from the cursor position to the last seed position. For textured images, the low-cost path may be sensitive to the cursor position, and more seeds are needed to achieve a satisfactory result. Boykov and Jolly [5] modeled segmentation as an energy minimization problem and used the graph-cut technique to solve the optimization problem. The user provides some hard constraints that indicate certain pixels to be parts of the object or the background. "GrabCut" extends the graph-cut segmentation [5] by reducing the human intervention to dragging a rectangle around the desired object. Freedman and Zhang [9] integrate a level-set based shape prior into graph-cut-based segmentation. Similar to [5], the user marks some pixels as parts of the object or the background.

An energy term related to the difference between the segmentation shape and the prior shape is added into the energy function. Incorporating such shape priors brings the benefit of handling blurred edges or multiple similar objects close to one another. "Lazy snapping" [12] provides a user-friendly tool for IS, which separates coarse and fine-scale processing to improve the performance. Duchenne et al. [28] used the user-supplied seeds

provided as a set of broad brush strokes as known pixel wise labels and inferred the remaining pixel labels by a statistical transductive inference. Although these interactive approaches are somewhat successful, most of them passively depend on the user to decide the next intervention and perform segmentation in a batch mode.

However, sometimes it might be difficult for the user to select the most important intervention. An automatic process that can suggest a useful user intervention and reduce the user's involvement would be more desirable. In addition, these existing approaches typically only integrate one type of the user's intervention, and the intervention is often done in an ad hoc way, often ignoring the current segmentation results. Moreover, the user's intervention is often provided as hard constraints without considering their uncertainties, and is usually provided before the segmentation starts. Mimicking the human's decision process, it may be more beneficial to be able to provide different types of interventions, to account for their uncertainties, to provide interventions at any time of the segmentation process, and to integrate the user's intervention with current segmentation results incrementally.

III. Page Style Work Nature of Previous System

To realize the goal of both automatic and interactive image segmentation, we need a model that can conveniently integrate image measurements, take the user's input, and systematically propagate its impact on the segmentation results. For this purpose a multilayer BN model to find object boundaries according to measurements of regions (super pixels), edges, vertices (junctions), and local constraints.

The local constraints capture our assumption that the object boundary should be locally smooth and have simple connectivity. Image segmentation is modeled as inferring the optimal states (e.g., on the object boundary or not) of these hidden variables from various measurements subject to constraints. The flowchart of our approach is illustrated in fig. 1. Given the edge map of an oversegmented image, we construct a multilayer BN to capture the local image regions, edge segments, vertices, and their relationships.

Various image measurements are then acquired, based on which an initial automatic segmentation is obtained through a probabilistic inference. For interactive image segmentation, the user examines the initial segmentation and provides appropriate interventions with/without the active input selection process. The influence of these user interventions on the states of other image entities is estimated through belief propagation. Finally, given the updated belief for each node, a probabilistic inference is performed to find the Most Probable Explanation (MPE) of the region and edge nodes. Based on the MPE result, the most likely configuration of the superpixel regions and the edge segments form the final segmentation.

A. Image Segmentation Framework

We use BN as the basic framework for image segmentation. We construct the BN model from an over segmentation of the image. Fig. 1 shows a concrete example. The edge map in the over segmentation consists of superpixel regions (i.e., the regional blobs), edge segments, and vertices. The multilayer BN models the causal relationships among the superpixel regions, edge segments, vertices, and angles. We build the BN model based on an edge map in the over segmentation of an image, which can be generated by any standard image segmentation approach such as watershed segmentation, normalized cuts, anisotropic diffusion.

The edge map consists of superpixel regions, edge segments, and vertices. Fig. 2(c) illustrates a multilayer BN that models the statistical relationships among these image entities. Specifically, the region layer contains all superpixel regions. The edge layer contains all edge segments, while the vertex layer contains all vertices. The region nodes, edge nodes, and vertex nodes have their image measurements. The measurements of regions can be any feature vector extracted from the statistics of the superpixel region. Local Smoothness Constraint[a], Simple Connectivity Constraint[a], Complete BN Model[a]

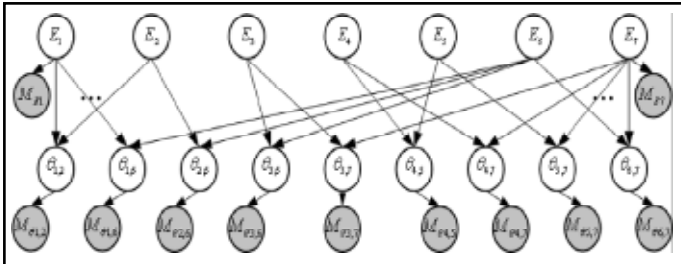


Fig. 1: BN with Angle Nodes to Impose the Local Smoothness Constraint

B. Interactive Image Segmentation

Fully automatic segmentation may not produce correct segmentation when the image data information cannot discriminate the boundary edges from nonboundary edges. Under such situations, the user's intervention can provide additional information to aid the automatic approach to produce correct segmentation. Existing IS approaches usually passively require the user to provide exact information such as labels for some edges, pixels, or regions. In contrast, we propose a new active input selection process that can improve both efficiency and accuracy of the IS.

1. Interactive Image Segmentation[a],
2. Active Input Selection[a]

IV. Proposed Model

Image segmentation is a difficult problem in computer vision. It aims at partitioning an image into constituent regions of interest. Many approaches have been proposed. We propose a new enhanced Bayesian Network (BN) model for both automatic and interactive image segmentation.

The proposed system works accurate for the set of images, The system accepts the input image and converts the image into split based three phase method and automatically finds the set of foreground, background and mixed multi layered structures, assign the master foreground and back ground structured pixels threshold by using bi-model histogram for the different set of segmentation by incorporating the Bayesian Network model for both automatic and interactive better image segmentation. The system set the segmentations in the form of hierarchal based on the region of the image for easy user's navigation of the segmentation. The system accepts the images and incorporates the BN model for both automatic and interactive segmentation.

A. Interactive Image Segmentation

For the interactive image segmentation, the user's interactions are incorporated as new evidence by instantiation of some nodes. Compared to the existing IS approaches, the intervention in our model can be given anytime, of different types, and can be applied incrementally. Moreover, the effect of the intervention on the states of other hidden nodes are systematically estimated via a principled probabilistic inference.

V. Experiments

A. Automatic Image Segmentation

We first tested our model for automatic segmentation on two sets of testing images: 1) 110 images from the Weizmann horse dataset [30] and 2) 45 cow images from the VOC2006 database [31]. The Weizmann dataset includes the side views of many horses that have different appearances and poses, which makes it challenging to segment them.

By visual inspection, we achieved reasonable results on these images. The errors mainly come from the appearance changes and the cluttering of background objects (e.g., the shadow) that have similar appearances as the horses. the error has been minimized in this approach.

To quantitatively evaluate the segmentation performance, we calculated the percentage of correctly labeled pixels (i.e., segmentation accuracy). Table I shows our results compared to three related works that also performed experiments on the Weizmann dataset [34-36]. Our automatic segmentation performance is ranked the second and just lower than [34], without using any shape prior, while both [34-35] used shape constraints. Our IS performance surpasses other approaches, which shows that even very limited user's intervention can significantly improve the segmentation performance. Passively IS and Actively IS[a] gives the slight reduced error rate with compare to the previous system.

VI. Conclusion

In this paper, we first propose a model-based segmentation approach based on BN. The BN systematically encodes the relationships among regions, edge segments, vertices, angles, and their measurements. The BN also models the local smoothness constraint and the simple connectivity constraint. Given the BN model, image segmentation is performed through belief propagation and probabilistic inference. The final segmentation is achieved by finding the MPE result that is consistent with all the measurements and constraints.

The proposed model is demonstrated to be able to perform fully automatic image segmentation, comparable to or outperforming several related methods. In addition, we further extend it to be used for interactive image segmentation. Specifically, we propose a new active input selection process to perform actively IS using the proposed BN model. This active selection can effectively improve the overall segmentation accuracy and reduce the total user's involvement. We demonstrate the concept of actively IS and compare it with passively IS.

Our experimental results demonstrate the promising capability of the proposed BN model for both automatic image segmentation and effective interactive image segmentation. The advantages of using a BN to model segmentation problems can be attributed to several aspects. First, it provides a systematic way to model the image segmentation problem in a probabilistic manner. Second, it is very convenient to incorporate new knowledge into the model due to the expressive and inference power of BNs.

Third, the user's intervention can be easily incorporated into the BN as new evidence in an incremental way. Unlike other IS methods, multiple types of the user's interventions can be added at any stage of the segmentation process. The impact of new evidence will be propagated throughout the whole network in a principled manner. These characteristics are very important, especially for the segmentation of complex images.

Finally, although our BN model is focused on the figure/ground segmentation problem, it can be easily extended to deal with multiclass segmentation. This extension can be done in two ways. First, we can design a series of BN models for segmenting each class versus the background. Applying these models will generate a multiclass segmentation. Second, we can extend the binary nodes (especially the region nodes) in the BN to discrete nodes with multiple states, allowing distinguishing multiple object classes. The local constraint such as the connectivity constraint should be changed accordingly since there could be complex boundaries in a multiclass segmentation. We plan to study this extension in future.

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