A Generic Probabilistic Graphical Model for Region-based Scene Interpretation

Michael Ying Yang
Institute for Information Processing, Leibniz University Hannover, Hannover, Germany

Keywords: Scene Interpretation, Energy Function, Conditional Random Field, Bayesian Network.

Abstract: The task of semantic scene interpretation is to label the regions of an image and their relations into meaningful classes. Such task is a key ingredient to many computer vision applications, including object recognition, 3D reconstruction and robotic perception. The images of man-made scenes exhibit strong contextual dependencies in the form of the spatial and hierarchical structures. Modeling these structures is central for such interpretation task. Graphical models provide a consistent framework for the statistical modeling. Bayesian networks and random fields are two popular types of the graphical models, which are frequently used for capturing such contextual information. Our key contribution is the development of a generic statistical graphical model for scene interpretation, which seamlessly integrates different types of the image features, and the spatial structural information and the hierarchical structural information defined over the multi-scale image segmentation. It unifies the ideas of existing approaches, e. g. conditional random field and Bayesian network, which has a clear statistical interpretation as the MAP estimate of a multi-class labeling problem. We demonstrate experimentally the application of the proposed graphical model on the task of multi-class classification of building facade image regions.

1 INTRODUCTION

The task of semantic scene interpretation is to label the regions of an image and their relations into semantically meaningful classes. Such task is a key ingredient to many computer vision applications, including object recognition, 3D reconstruction and robotic perception. The problem of scene interpretation in terms of classifying various image components in the images is a challenging task partially due to the ambiguities in the appearance of the image data (Tsotsos, 1988). These ambiguities may arise either due to the physical conditions such as the illumination and the pose of the scene components with respect to the camera, or due to the intrinsic nature of the data itself. Images of man-made scenes, e. g. building facade images, exhibit strong contextual dependencies in the form of spatial and hierarchical interactions among the components. Neighboring pixels tend to have similar class labels, and different regions appear in restricted spatial configurations. Modeling these spatial and hierarchical structures is crucial to achieve good classification accuracy, and help alleviate the ambiguities.

Graphical models, either directed models or undirected models, provide consistent frameworks for the statistical modeling. Two types of graphical models are frequently used for capturing such contextual information, i. e. Bayesian networks (BNs) (Sarkar & Boyer, 1993) and random fields (RFs) (Besag, 1974), corresponding to directed and undirected graphs. RFs mainly capture the mutually dependent relationships such as the spatial correlation. Attempts were made to exploit the spatial structure for semantic image interpretation by using RFs. Early since nineties, Markov random fields (MRFs) have been used for image interpretation (Modestino & Zhang, 1992); the limiting factor that MRFs only allow for local features has been overcome by conditional random fields (CRFs) (Kumar & Hebert, 2003a; Lafferty *et al.*, 2001), where arbitrary features can be used for classification, at the expense of a purely discriminative approach. On the other side, BNs usually model the causal relationships among random variables. Early in nineties, (Sarkar & Boyer, 1993) have proposed the perceptual inference network with the formalism based on Bayesian networks for geometric knowledge-base representation. Both have been used to solve computer vision problems, yet they have their own limitations in representing the relationships

Yang M..
A Generic Probabilistic Graphical Model for Region-based Scene Interpretation.
DOI: 10.5220/0005341004860491
In *Proceedings of the 10th International Conference on Computer Vision Theory and Applications* (VISAPP-2015), pages 486-491
ISBN: 978-989-758-090-1

between random variables. BNs are not suitable to represent symmetric relationships that mutually relate random variables. RFs are natural methods to model symmetric relationships, but they are not suitable to model causal or part-of relationships.

Spatial and hierarchical relationships are two valuable cues for image interpretation of man-made scenes. In this paper we will develop a consistent graphical model representation for image interpretation that includes both information about the spatial structure and the hierarchical structure. We assume some preprocessing leads to regions, either as a partitioning of the image area or as a set of overlapping or non-overlapping segments. The key idea for integrating the spatial and the hierarchical structural information into the interpretation process is to combine them with the low-level region class probabilities in a classification process by constructing the graphical model on the multi-scale image regions.

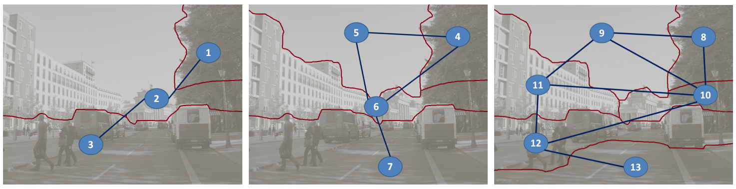
The following sections are organized as follows. The related works are discussed in Sec. 2. In Sec. 3, the statistical model for the interpretation problem is formulated. Then, the relations to previous models is discussed in Sec. 4. In Sec. 5, experimental results are presented. Finally, this work is concluded in Sec. 6.

2 RELATED WORK

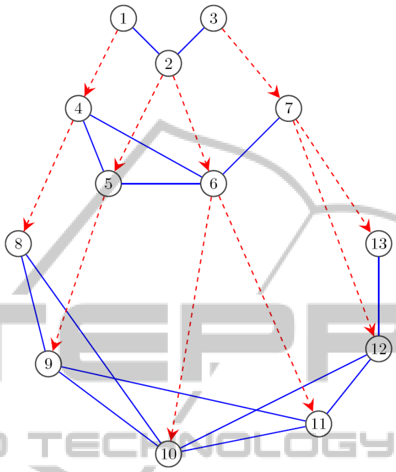
There are many recent works on contextual models that exploit the spatial structures in the image. Meanwhile, the use of multiple different over-segmented images as a preprocessing step is not new to computer vision. In the context of multi-class image classification, the work of (Plath *et al.*, 2009) comprises two aspects for coupling local and global evidences both by constructing a tree-structured CRF on image regions on multiple scales and using global image classification information. Thereby, (Plath *et al.*, 2009) neglect direct local neighborhood dependencies. The work of (Schnitzspan *et al.*, 2008) extends classical one-layer CRF to a multi-layer CRF by restricting the pairwise potentials to a regular 4-neighborhood model and introducing higher-order potentials between different layers.

Although not as popular as CRFs, BNs have also been used to solve computer vision problems (Mortensen & Jia, 2006; Sarkar & Boyer, 1993). BNs provide a systematic way to model the causal relationships among the entities. By explicitly exploiting the conditional independence relationships (known as prior knowledge) encoded in the structure, BNs could simplify the modelling of joint probability distributions. Based on the BN structure, the joint probability is decomposed into the product of a set of local conditional probabilities, which is much easier to specify because of their semantic meanings (Zhang & Ji, 2010).

Graphical models have reached a state where both hierarchical and spatial neighborhood structures can be efficiently handled. RFs and BNs are suitable for representing different types of statistical relationships among the random variables. Yet only a few previous works focus on integrating RFs with BNs. In (Kumar & Hebert, 2003b), the authors present a generative model based approach to man-made structure detection in 2D natural images. They use a causal multiscale random field as a prior model on the class labels. Labels over an image are generated using Markov chains defined over coarse to fine scales. However, the spatial neighborhood relationships are only considered at the bottom scale. So, essentially, this model is a tree-structured belief network plus a flat Markov random field. Recently, a unified graphical model that can represent both the causal and noncausal relationships among the random variables is proposed in (Zhang & Ji, 2010). They first employ a CRF to model the spatial relationships among the image regions and their measurements. Then, they introduce a multilayer BN to model the causal dependencies. The CRF model and the BN model are then combined through the theories of the factor graphs to form a unified probabilistic graphical model. Their graphical model is too complex in general. Although their model improves state of the art results on the Weizmann horse dataset and the MSRC dataset, they need a lot of domain expert knowledge to design the local constraints. Also, they use a combination of supervised parameter learning and manual parameter setting for the model parameterization. Simultaneously learn the BN and CRF parameters automatically from the training data is not a trivial task. Compared to the graphical models in (Kumar & Hebert, 2003b), which are too simple, the graphical models in (Zhang & Ji, 2010) are too complex in general. Our graphical model lies in between, cf. Fig. 1. We try to construct our graphical model that is not too simple in order to model the rich relationships among the neighborhood of pixels and image regions in the scene, yet not too complex in order to make parameter learning and probabilistic inference efficiently. Furthermore, our model underlies a clear semantic meaning. If the undirected edges are ignored, meaning no spatial relationships are considered, the graph is a tree representing the hierarchy of the partonomy among the scales. Within each scale, the spatial regions are connected by the pairwise edges.



(a) Multi-scale segmentation



(b) The graphical model

Figure 1: Illustration of the graphical model architecture. The blue edges between the nodes represent the neighborhoods at one scale (undirected edges), and the red dashed edges represent the hierarchical relation between regions (undirected or directed edges).

3 MODEL

3.1 The Graphical Model Construction

By constructing the graphical model, we can flexibly choose either directed edges or undirected edges to model the relationships between the random variables based on the semantic meaning of these relationships.

We use an example image to explain this model construction process. Given a test image, Fig. 1 shows the corresponding multi-scale segmentation of the image, and the corresponding graphical model for image interpretation. Three layers are connected via a region hierarchy (Drauschke & Förstner, 2011). The development of the regions over several scales is used to model the region hierarchy. Furthermore, the relation is defined over the maximal overlap of the regions. Nodes connection and numbers correspond to the multi-scale segmentation. The pairwise interactions between the spatial neighboring regions can be modeled by the undirected edges. The pairwise potential functions can be defined to capture the similarity between the neighboring regions. The hierarchical relation between regions of the scene partonomy representing parent-child relations or part-of relations can be modeled by either the undirected edges or the directed edges.

3.2 Multi-class Labeling Representation

We present the scene interpretation problem as a multi-class labeling problem. Given the observed data d, the distribution P over a set of the variables x can be expressed as a product of the factors

$$P(x \mid d) = \frac{1}{Z} \prod_{i \in \mathcal{V}} f_i(x_i \mid d) \prod_{\{i,j\} \in \mathcal{E}} f_{ij}(x_i, x_j \mid d) \prod_{\langle i,k \rangle \in \mathcal{S}} f_{ik}(x_i, x_k \mid d) \tag{1}$$

where the factors f_i, f_{ij}, f_{ik} are the functions of the corresponding sets of the nodes, and Z is the normalization factor. The set $\mathcal{V}$ is the set of the nodes in the complete graph, and the set $\mathcal{E}$ is the set of pairs collecting the neighboring nodes within each scale. $\mathcal{S}$ is the set of pairs collecting the parent-child relations between regions with the neighboring scales, where $\langle i,k \rangle$ denotes nodes i and k are connected by either a undirected edge or a directed edge. Note that this model only exploits up to second-order cliques, which makes learning and inference much faster than the model involving high-order cliques.

By simple algebra calculation, the probability distribution given in Eq. (1) can be written in the form of a *Gibbs* distribution

$$P(x \mid d) = \frac{1}{Z} \exp\left(-E(x \mid d)\right) \tag{2}$$

with the energy function $E(x \mid d)$ as

$$\begin{aligned} E(x \mid d) = \sum_{i \in \mathcal{V}} E_1(x_i \mid d) + \alpha \sum_{\{i,j\} \in \mathcal{E}} E_2(x_i, x_j \mid d) \\ + \beta \sum_{\langle i,k \rangle \in \mathcal{S}} E_3(x_i, x_k \mid d) \end{aligned} \tag{3}$$

where α and β are the weighting coefficients in the model. E_1 is the unary potential, E_2 is the pairwise potential, and E_3 is either the hierarchical pairwise potential or the conditional probability energy. This graphical model is illustrated in Fig. 1. The most probable or maximum a posteriori (MAP) labeling x^* is defined as

$$x^* = \arg\max_{x \in \mathcal{L}^n} P(x \mid d) \tag{4}$$

and can be found by minimizing the energy function $E(x \mid d)$.

4 RELATION TO PREVIOUS MODELS

In this section, we draw comparisons with the previous models for image interpretation (Drauschke & Förstner, 2011; Fulkerson *et al.*, 2009; Plath *et al.*, 2009; Yang *et al.*, 2010) and show that at certain choices of the parameters of our framework, these methods fall out as the special cases. We will now show that our model is not only a generalization of the standard flat CRF over the image regions, but also of the hierarchical CRF and the conditional Bayesian network.

4.1 Equivalence to Flat CRFs Over Regions

Let us consider the case with only one layer segmentation of the image (the bottom layer of the graphical model in Fig. 1). In this case, the weight β is set to be zero, the set $\mathcal{V}^1$ is the set of nodes in the graph of the bottom layer, and the set $\mathcal{E}^1$ is the set of pairs collecting the neighboring nodes in the bottom layer. This allows us to rewrite (3) as

$$E(x \mid d) = \sum_{i \in \mathcal{V}^1} E_1(x_i \mid d) + \alpha \sum_{\{i,j\} \in \mathcal{E}^1} E_2(x_i, x_j \mid d) \tag{5}$$

which is exactly the same as the energy function associated with the flat CRF defined over the image regions with E_1 as the unary potential and E_2 as the pairwise potential. In this case, our model becomes equivalent to the flat CRF models defined over the image regions (Fulkerson *et al.*, 2009; Gould *et al.*, 2008).

4.2 Equivalence to Hierarchical CRFs

Let us now consider the case with the multi-scale segmentation of the image. If we choose E_3 as a pairwise potential in (3), the energy function reads

$$\begin{aligned} E(x \mid d) = \sum_{i \in \mathcal{V}} E_1(x_i \mid d) + \alpha \sum_{\{i,j\} \in \mathcal{E}} E_2(x_i, x_j \mid d) \\ + \beta \sum_{\{i,k\} \in \mathcal{S}} E_3(x_i, x_k \mid d) \end{aligned} \tag{6}$$

which is exactly the same as the energy function associated with the hierarchical CRF defined over the multi-scale of the image regions with E_1 as the unary potential, E_2 as the pairwise potential within each scale, and E_3 as the hierarchical pairwise potential with the neighboring scales. In this case, our model becomes equivalent to the hierarchical CRF models defined over multi-scale of image regions (He *et al.*, 2004; Yang *et al.*, 2010).

If we set α to be zero, and choose E_3 as a pairwise potential in (3), the energy function reads

$$E(x \mid d) = \sum_{i \in \mathcal{V}} E_1(x_i \mid d) + \beta \sum_{\{i,k\} \in \mathcal{S}} E_3(x_i, x_k \mid d) \tag{7}$$

which is the same as the energy function associated with the tree-structured CRF by neglecting the direct local neighborhood dependencies on the image regions on multiple scales. In this case, our model becomes equivalent to the tree-structured CRF models defined over multi-scale of the image regions (Plath *et al.*, 2009; Reynolds & Murphy, 2007).

4.3 Equivalence to Conditional Bayesian Networks

If we set α to be zero, and choose E_3 as the conditional probability energy in (3), the energy function reads

$$E(x \mid d) = \sum_{i \in \mathcal{V}} E_1(x_i \mid d) + \beta \sum_{\langle i,k \rangle \in \mathcal{S}} E_3(x_i, x_k \mid d) \tag{8}$$

which is the same as the energy function associated with the tree-structured conditional Bayesian network defined over the multi-scale of the image regions. In the tree-structured conditional Bayesian network, the classification of a region is based on the unary features derived from the region and the binary features derived from the relations of the region hierarchy graph. In this case, our model becomes equivalent to the tree-structured conditional Bayesian network defined over multi-scale of the image regions (Drauschke & Förstner, 2011).

5 EXPERIMENTS

We conduct the experiments to evaluate the performance of the proposed model on eTRIMS dataset (Korč & Förstner, 2009). The dataset consists of 60 building facade images, labeled with 8 classes: *building*, *car*, *door*, *pavement*, *road*, *sky*, *vegetation*, *window*. We randomly divide the images into a training set with 40 images and a testing set with 20 images. In all experiments, we take the ground truth label of a region to be the majority vote of the ground truth pixel labels. At the test stage we compute our accuracy at the pixel level.

The hierarchical mixed graphical model is defined over the multi-scale of the image regions when we choose E_3 as the conditional probability energy in Eq. (3). We present the experimental results for the hierarchical mixed graphical model with multi-scale mean shift segmentation (Comaniciu & Meer, 2002) and watershed segmentation (Vincent & Soille, 1991), and the comparison with the baseline region classifier, the flat CRF, and the hierarchical CRF classification results.

Results with Multi-scale Mean Shift and the Hierarchical Mixed Graphical Model. The overall classification accuracy is 68.9%. The weighting parameters are $\alpha = 0.8$, $\beta = 1$. For comparison, the RDF region classifier gives an overall accuracy of 58.8%, the flat CRF gives an overall accuracy of 65.8%, and the hierarchical CRF gives an overall accuracy of 69.0%.

Qualitative results of the hierarchical mixed graphical model with the multi-scale mean shift on the eTRIMS dataset (Korč & Förstner, 2009) are presented in Fig. 2. The qualitative inspection of the results in these images shows that the hierarchical mixed graphical model yields significant improvement. The hierarchical mixed graphical model yields more accurate and cleaner results than the flat CRF and the RDF region classifier, and comparable to the hierarchical CRF model. The greatest accuracies are for classes which have low visual variability and many training examples (such as window, vegetation, building, and sky) whilst the lowest accuracies are for classes with high visual variability or few training examples (for example door, car, and pavement). We expect more training data and the use of features with better invariance properties will improve the classification accuracy. Objects such as car, door, pavement, and window are sometimes incorrectly classified as *building*, due to the dominant presence of the building in the image. Detecting windows, cars, and doors should resolve some of such ambiguities.

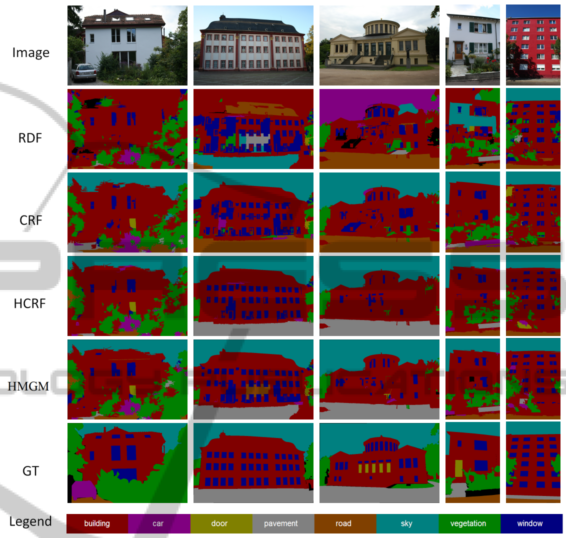


Figure 2: Qualitative classification results of the hierarchical mixed graphical model with the multi-scale mean shift segmentation on the testing images from the eTRIMS dataset (Korč & Förstner, 2009).

Results with Multi-scale Watershed and the Hierarchical Mixed Graphical Model. The overall classification accuracy is 68.0%. The weighting parameters are $\alpha = 1.08$, $\beta = 1$. For comparison, the RDF region classifier gives an overall accuracy of 55.4%, the flat CRF gives an overall accuracy of 61.8%, and the hierarchical CRF gives an overall accuracy of 65.3%. Qualitative results of the hierarchical mixed graphical model on the eTRIMS dataset are presented in Fig. 3.

6 CONCLUSION

In this paper, we have addressed the problem of incorporating two different types of the contextual information, namely the spatial structure and the hierarchical structure for image interpretation of man-made scenes. We propose a statistically motivated, generic probabilistic graphical model framework for scene interpretation, which seamlessly integrates different types of the image features, and the spatial

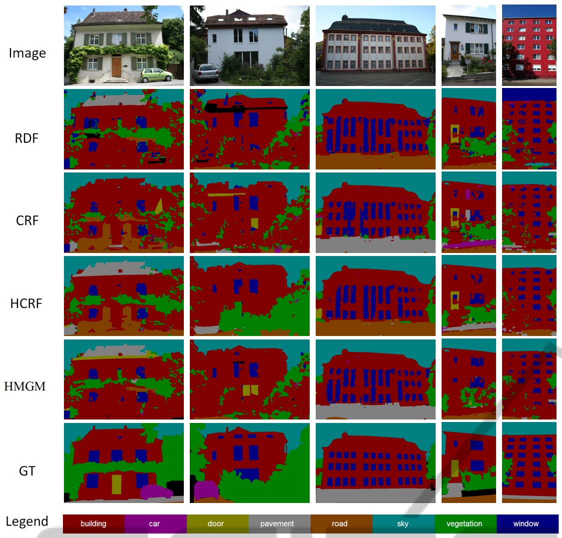


Figure 3: Qualitative classification results of the hierarchical mixed graphical model with the multi-scale watershed segmentation on the testing images from the eTRIMS dataset (Korč & Förstner, 2009).

structural information and the hierarchical structural information defined over the multi-scale image segmentation. We demonstrate the application of the proposed model on the building facade image classification task.

REFERENCES

Besag, J. 1974. Spatial interaction and the statistical analysis of lattice systems (with discussion). *Journal of the royal statistical society*, B-36(2), 192–236.

Comaniciu, Dorin, & Meer, Peter. 2002. Mean shift: A robust approach toward feature space analysis. *Ieee transactions on pattern analysis and machine intelligence*, 24(5), 603–619.

Drauschke, M., & Förstner, W. 2011. A bayesian approach for scene interpretation with integrated hierarchical structure. *Pages 1–10 of: Annual symposium of the german association for pattern recognition (dagm)*.

Fulkerson, B., Vedaldi, A., & Soatto, S. 2009. Class segmentation and object localization with superpixel neighborhoods. *Pages 670–677 of: International conference on computer vision*.

Gould, S., Rodgers, J., Cohen, D., Elidan, G., & Koller, D. 2008. Multi-class segmentation with relative location prior. *International journal of computer vision*, 80(3), 300–316.

He, X., Zemel, R., & Carreira-perpin, M. 2004. Multiscale conditional random fields for image labeling. *Pages 695–702 of: Ieee conference on computer vision and pattern recognition*.

Korč, Filip, & Förstner, Wolfgang. 2009. eTRIMS Image Database for interpreting images of man-made scenes. *In: Tr-igg-p-2009-01, department of photogrammetry, university of bonn*.

Kumar, Sanjiv, & Hebert, Martial. 2003a. Discriminative random fields: A discriminative framework for contextual interaction in classification. *Pages 1150–1157 of: Ieee international conference on computer vision*, vol. 2.

Kumar, Sanjiv, & Hebert, Martial. 2003b. Man-made structure detection in natural images using a causal multiscale random field. *Pages 119–126 of: Ieee conference on computer vision and pattern recognition*.

Lafferty, J., McCallum, A., & Pereira, F. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. *Pages 282–289 of: International conference on machine learning*.

Modestino, J. W., & Zhang, J. 1992. A markov random field model-based approach to image interpretation. *Ieee transactions on pattern analysis and machine intelligence*, 14(6), 606–615.

Mortensen, Eric N., & Jia, Jin. 2006. Real-time semi-automatic segmentation using a bayesian network. *Pages 1007–1014 of: Ieee conference on computer vision and pattern recognition*.

Plath, Nils, Toussaint, Marc, & Nakajima, Shinichi. 2009. Multi-class image segmentation using conditional random fields and global classification. *Pages 817–824 of:* Bottou, Léon, & Littman, Michael (eds), *International conference on machine learning*.

Reynolds, J., & Murphy, K. 2007. Figure-ground segmentation using a hierarchical conditional random field. *Pages 175–182 of: Canadian conference on computer and robot vision*.

Sarkar, S., & Boyer, K. L. 1993. Integration, inference, and management of spatial information using bayesian networks: Perceptual organization. *Pami*, 15, 256–274.

Schnitzspan, P., Fritz, M., & Schiele, B. 2008. Hierarchical support vector random fields: Joint training to combine local and global features. *Pages 527–540 of:* Forsyth, D., Torr, P., & Zisserman, A. (eds), *European conference on computer vision*.

Tsotsos, J.K. 1988. A 'complexity level' analysis of immediate vision. *International journal of computer vision*, 2(1), 303–320.

Vincent, Luc, & Soille, Pierre. 1991. Watersheds in digital spaces: An efficient algorithm based on immersion simulations. *Ieee transactions on pattern analysis and machine intelligence*, 13(6), 583–598.

Yang, Michael Ying, Förstner, Wolfgang, & Drauschke, Martin. 2010. Hierarchical conditional random field for multi-class image classification. *Pages 464–469 of: International conference on computer vision theory and applications*.

Zhang, Lei, & Ji, Qiang. 2010. Image segmentation with a unified graphical model. *Pami*, 32(8), 1406–1425.