Probabilistic Cascade Random Fields for Man-Made Structure Detection

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Abstract. This paper develops the probabilistic version of cascade algorithm, specifically, Probabilistic AdaBoost Cascade (PABC). The proposed PABC algorithm is further employed to learn the association potential in the Discriminative Random Fields (DRF) model, resulting the Probabilistic Cascade Random Fields (PCRF) model. PCRF model enjoys the advantage of incorporating far more informative features than the conventional DRF model. Moreover, compared to the original DRF model, PCRF is less sensitive to the class imbalance problem. The proposed PABC and PCRF were applied to the task of man-made structure detection. We compared the performance of PABC with different settings, the performance of the original DRF model and that of PCRF. Detailed numerical analysis demonstrated that PABC improves the performance with more AdaBoost nodes, and the interaction potential in PCRF further improves the performance significantly.

1 Introduction

Traditional pattern classification methods assume that the class labels are independent to each other. However, in real life data (e.g. sequences, images, videos), the labels of the adjacent data points are correlated. This suggests us take account of the label dependencies in designing classifiers for real life data. For example, Markov Random Fields (MRF) [6], Conditional Random Fields (CRF) [4], and Discriminative Random Fields (DRF) [9], improve the performance of an i.i.d. classification technique by taking into account the spatial dependencies.

In this paper, we are primarily interested in classifying elements (pixels or regions) of a two-dimensional image. Let $\mathbf{X}$ be the observed data from an input image, where $\mathbf{X} = \{\mathbf{x}_i\}_{i\in S}$ with $\mathbf{x}_i$ being the data from the i^{th} image site, and S is the set of all the image sites. Let the corresponding labels for the image be $\mathbf{Y} = \{y_i\}_{i\in S}$, where y_i is the label for image site i.

MRF is usually used in the generative model framework which models the joint distribution of the observed data and the labels. The posterior of the labels given the data can be expressed by Bayes' rule as

$$P(\mathbf{Y}|\mathbf{X}) \propto P(\mathbf{X}, \mathbf{Y}) = P(\mathbf{X}|\mathbf{Y})P(\mathbf{Y}). \tag{1}$$

H. Zha, R.-i. Taniguchi, and S. Maybank (Eds.): ACCV 2009, Part II, LNCS 5995, pp. 596–607, 2010.

The prior distribution of the labels, $P(\mathbf{Y})$, is modelled as MRF. However, the likelihood term, $P(\mathbf{X}|\mathbf{Y})$, is usually very complicated, and it is a distribution in a high-dimensional space (since the image data $\mathbf{X}$ is of high dimension). Thus, it is usually very difficult, if not impossible, to find a good model for $P(\mathbf{X}|\mathbf{Y})$.

On the other hand, CRF and DRF are employed in the discriminative model framework, in which we directly model the posterior distribution of the labels given the data, $P(\mathbf{Y}|\mathbf{X})$. CRF was proposed in the context of segmentation and labelling of 1D sequences, and DRF is generalized version of CRF for 2D image data.

There are two components in DRF model, namely, the association potential and the interaction potential (see Section 2 for details about DRF model). The association potential models the local evidence which ignores the neighborhood information. In [9], the association potential was modelled by a logistic regression classifier, which can only incorporate a limited number of features, leading to restricted classification capability.

AdaBoost [2] is a classification framework which has appealing theoretical properties, and has shown impressive empirical results in a wide variety of tasks, for example, face detection [15,16,17]. This paper takes the advantage of the power of AdaBoost to incorporate more informative features for learning the association potential in DRF, thus overcoming the limitations of logistic regression model in [9]. In the learning stage, we face the problem of unbalanced training set, i.e. far less positive examples than negative examples. AdaBoost cascade [15,16,17] and WaldBoost [13] are usually used to solve this problem. However, the aforementioned methods give a results in $\{-1, 1\}$, while we need a real number for the association potential, which is the logarithm of a probability value as in [9]. To achieve this purpose, we develop Probabilistic version of AdaBoost Cascade (PABC), which calculates the posterior probability of class label when a testing example is presented. PABC is employed to learn the association potential in DRF model, and the interaction potential is learned in the same way as in the original DRF model [9]. The resulting model, Probabilistic Cascade Random Fields (PCRF), enjoys the capability of incorporating far more informative features and a more powerful association potential than the conventional DRF model.

The proposed PCRF was applied to man-made structure detection problem. We compared the performance of PABC with different settings, the performance of the original DRF model and the performance of PCRF. Detailed quantitative measures demonstrate that with more AdaBoost nodes, the overall performance of PABC improves, and with the information from interaction potential, PCRF further removes some false positives and fills in some missing parts of the object.

2 Review of Discriminative Random Fields

Discriminative Random Fields (DRF) model [9] avoids the independence assumption and seek to model the conditional joint distribution of the labels if the data is given, i.e., $P(\mathbf{Y}|\mathbf{X})$. DRF model defines the conditional probability of the labels $\mathbf{Y}$ as: