JOINT SEGMENTATION AND RECOGNITION OF LICENSE PLATE CHARACTERS

Xin Fan[1,2], *Guoliang Fan*[1]

[1]School of Electrical and Computer Engineering
Oklahoma State University
Stillwater, OK, 74078, USA

Dequn Liang[2]

[2]School of Information Engineering
Dalian Maritime University
Dalian, 116026, China

ABSTRACT

The segmentation and recognition modules are usually implemented sequentially in most traditional automatic license recognition (LPR) systems. In this work, we integrate segmentation and recognition into a Markov network, where bidirectional constraints between segmentation and recognition are exploited for LPR. In addition, both low-level structural attributes and compositional semantics of license plates are incorporated in a probabilistic way. A belief propagation (BP) algorithm is used for statistical inference that is able to separate and recognize license characters simultaneously. Experiments on Chinese license plates show that the proposed approach work well even when connected and distorted characters present.

***Index Terms*—** Automatic license plate recognition, character image segmentation and recognition, Markov network, belief propagation

1. INTRODUCTION

Automatic license plate recognition (LPR) plays an important role in numerous transportation applications such as automatic toll payment, parking lots management and traffic surveillance [1]. A typical LPR system is composed of three major stages, i.e., license plate localization, character segmentation and character recognition. In this paper, we focus on a new approach to jointly integrating the latter two stages.

The low-level processing techniques, e.g., histogram projection [2], morphology [3] and the hough transformation [4], dominate the studies on separating license plate characters. The success of these techniques is largely owing to the structural characteristics of license plates, including the direction of characters, the regular interval between characters and the fixed license numbers. For example, the algorithm in [2] utilizes the attributes of horizontal plates and evenly distributed characters, and the adaptive morphological approach proposed in [3] employs the geometric information of license plates. In the context of optical character-recognition (OCR), a large number of methods have been presented to identify the segmented characters, such as neural networks [1, 5], Hausdorff distance [6] and template matching [7]. High recognition rates were reported by these OCR algorithms if they are given well segmented character images as the input.

Most automatic LPR systems cascade the modules of segmentation and recognition in a sequential manner. These cascade approaches arise such a dilemma that an accurate recognizer may provide useful cues for a good segmentation while a correct recognizer demands well segmented inputs. In the applications of handwritten OCR, researchers have made some attempts to feed outputs of recognizers back to segmentation algorithms [5, 8]. Recognition results are then incorporated into segmentation algorithms in order to validate the segmented candidates through accept/reject decisions [5] or to tune the parameters necessary for segmentation [8]. These joint segmentation and recognition approaches are more robust to deal with character distortions.

We notice that an automatic LPR system would benefit from either the low-level structural constrains of licence plates or the high-level information given by the recognizers. In this paper, we propose a graphical model, i.e, a two-layer Markov network [9], to integrate segmentation and recognition into one framework. Both the low-level and high-level constraints are incorporated in terms of probabilities in contrast to the previous work where these constraints are applied to perform binary decisions (accept/reject) on candidates. The segmentation and recognition results turn out to be marginal probability density estimation, which can be achieved by a belief propagation (BP) algorithm. The licence plate characters are segmented and recognized simultaneously as the outputs of the inference algorithm.

2. PROBLEM FORMULATION

In this paper, we investigate the approach to the segmentation and recognition of license plate characters. We assume the position and the size of the license plate in an image is determined *a prior* by a plate localization algorithm. And the license plate is rectified by a skew correction algorithm

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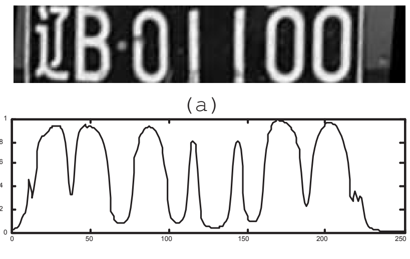


Fig. 1. An example of input images and its vertical projection histogram (smoothed by a 1-D Gaussian kernel).

so that the characters are horizontally distributed, but some distortions and corruptions may appear in input images. An example of the input image is shown in Fig. 1(a). We first list the low-level and high-level constraints beneficial to robust segmentation and recognition, and then present a graphical model that incorporates these constraints into segmentation and recognition.

2.1. Low-level and high-level constraints

Such attributes of license plate characters like gray intensity, edge and position provide low-level cues for character segmentation. What we utilize in our approach includes:

- The characters of a license plate have high contrast to the background and each character occupies a certain region of a plate. The vertical projection histogram (shown in Fig. 1(b)) counting the number of edge points in each column is such a good description of this constraint that many segmentation algorithm have been developed based on analyzing the histogram [2, 3].
- The intervals between characters are uniform.

We state the following semantic attributes of a license plate as the high-level constrains:

- A license plate has a fixed number of characters. In this study, the license plates have six characters. [1]
- The characters of a license plate have compositional semantics [5]. The first character of a valid Chinese plate is an alphabetical character and the last three are digits.

In addition, we consider the intermediate constraint that bridges segmentation and recognition. The segmented character images are readable, that is, the recognizers would have valid outputs with the input of the segmented images [5, 10]. All these constraints are incorporated by means of a probabilistic model.

[1] A Chinese license plate has seven characters, the first of which is a Chinese character. We leave the first one out for the sake of the generalization of our approach to the western plates.

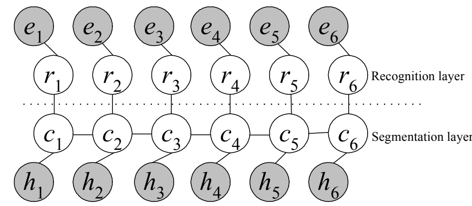


Fig. 2. Two-layer Markov network to integrate segmentation and recognition.

2.2. Graphical model for joint segmentation and recognition

We formulate the problem of segmenting and recognizing license characters as the probabilistic estimation. The variables representing the recognized labels are denoted as $\boldsymbol{r}$, a random vector with six components. Each component r_i takes a discrete value from a set with 36 elements standing for 10 digits and 26 letters. We use $\boldsymbol{c}$, also a 6-dimensional vector, to denote the horizontal positions of license characters as the segmentation variables since these positions can determine the character regions of interest (ROIs) in plate images based on the assumptions of known orientation and size of a plate. We pose segmentation and recognition as the one to find the values that maximize a posterior probability (MAP), $p(\boldsymbol{r}|\boldsymbol{Y})$ and $p(\boldsymbol{c}|\boldsymbol{Y})$, given a license image $\boldsymbol{Y}$.

A Markov network encodes the pair-wise probabilistic dependencies between random variables [9]. The joint probability of latent variables $\boldsymbol{X}(\boldsymbol{X} = [\boldsymbol{c}, \boldsymbol{r}])$ and observations $\boldsymbol{Y}$ is represented in terms of dependent functions as:

$$p(\boldsymbol{X}, \boldsymbol{Y}) = \frac{1}{Z} \prod_{(i,j)} \psi(x_i, x_j) \prod_{i} \phi(x_i, y_i), \qquad (1)$$

where Z is a normalization constant, $\psi(\cdot)$ is the compatible function between latent variables and $\phi(\cdot)$ is the potential function giving the evidence for x_i from observations. The dependencies describing the constraints of license plates are graphically represented as a two-layer Markov network shown in Fig. 2, where empty circles are the hidden variables whereas filled ones denote observations. The empty nodes at the top layer, that we state as recognition layer, represent the labels r_i of the six characters to be recognized and those at the lowest layer (segmentation layer) depict the positions of the characters. The observations of the segmentation layer are the projection histogram h_i, while those of the recognition layer are edges in ROIs and the prior information e_i. Recalling (1), the joint probability $p(\boldsymbol{r}, \boldsymbol{c}, \boldsymbol{Y})$ is fully determined by the compatible functions ($\psi(c_i, r_j)$ and $\psi(c_i, c_j)$) and the potential function ($\phi(r_i, y_i)$ and $\phi(c_i, y_i)$). In this study, these functions are derived from the constraints in Section 2.1.

The potential $\phi(c_i, y_i)$ represent how likely a character locates at a certain position c_i given an plate image. It can be seen from Fig. 1(b) that the projection histogram provides such an index of where a character position should be. We specify $\phi(c_i, y_i)$ as:

$$\phi(c_i, y_i) = H(c_i), \tag{2}$$

where $H(c_i)$ is the projection histogram value at c_i.

The compatible function $\psi(c_i, r_j)$ evaluates the probabilities of the labels of the ROI image centered at c_j to be recognized. These values can be calculated by any character recognition algorithms. We adopt a template matching algorithm by comparing the similarity of the shape contexts between the character templates and ROI images [7] so that the function $\psi(c_i, r_j)$ is defined as:

$$\psi(c_i, r_j) = \frac{1}{d(T_{sc}(r_i), I_{sc}(c_i)) + \delta}, \tag{3}$$

where $d(\cdot, \cdot)$ is a distance metric, δ is a small positive value to avoid a division by zero, $T_{sc}(r_i)$ and $I_{sc}(c_i)$ are the shape contexts of the templates and the ROI image respectively.

The compatible function $\psi(c_i, c_j)$ specifies the interactions between the positions of characters. We enforce a Gaussian density to the character distance to apply the regular interval constraint:

$$\psi(c_i, c_j) = \frac{1}{\sqrt{2\pi}\sigma_c} \exp(-\frac{(d_c(c_i, c_j) - D_e)^2}{2\sigma_c^2}), \tag{4}$$

where $d_c(\cdot, \cdot)$ is the Euclidean distance between two positions and D_e is the mean distance of the character intervals. We introduce the variance $\sigma_c = D_e/2$ to accommodate the variations brought by camera perspective distortions.

The potential $\phi(r_i, y_i)$ describes the probability of a certain character presenting in license plates. We specify this potential according to the compositional semantics in Section 2.1. For example, the potential of the first label $\phi(r_1)$ can be specified as:

$$\phi(r_1) = \begin{cases} 0 & \text{if } 0 \leqslant r_1 \leqslant 9 \\ \frac{1}{26} & \text{otherwise} \end{cases}. \tag{5}$$

Alternatively, this potential can be obtained by counting the occurrence frequency of the characters in a licence plate database.

All the constraints discussed in Section 2.1 form the joint probability (1). The potential $\phi(c_i, y_i)$ and the compatible function $\psi(c_i, c_j)$ embody the low-level structural constraints. The number of variables (nodes) in each layer as well as $\phi(r_i, y_i)$ imply high-level constraints. The intermediate constraint is embedded in $\psi(c_i, r_j)$. With the joint probability available, we can achieve segmentation and recognition by using the BP algorithm to marginalize the joint probability, i.e., to obtain $p(\boldsymbol{r}|\boldsymbol{Y})$ and $p(\boldsymbol{c}|\boldsymbol{Y})$.

3. INFERENCE ALGORITHM

The inference can be accomplished by the BP algorithm if there is no loop in the Markov network as our model. The BP algorithm accumulates local computations to circumvent global computations. The key step of the BP algorithm is to recursively updating the following local messages from the jth node to the ith one [9]:

$$m_{ij}(x_j) \leftarrow \sum_{x_i} \phi_i(x_i, y_i)\psi(x_i, x_j) \prod_{k \in N(i)\backslash j} m_{ki}(x_i), \tag{6}$$

where $N(i)\backslash j$ denotes the neighboring nodes of the ith except for the jth. Once all the messages to the current node are available, the marginal probability of the current node is computed as the "belief", $b(x_i)$:

$$b(x_i) \propto \phi(x_i, y_i) \prod_{j \in N(i)} m_{ji}(x_i). \tag{7}$$

The algorithm converges when all the nodes have been visited.

The standard BP algorithm requires the discretization of variables and probabilities. In our application, the variables in the recognition layer are discrete. We take every two column numbers near the peaks of the projection histogram as the possible values of the segmentation variables.

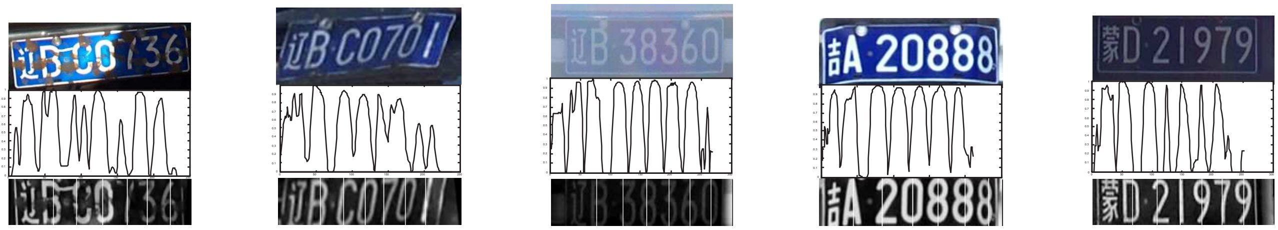
4. EXPERIMENTAL RESULTS

The DLL implementation of the proposed method and the compared algorithms are available at our webpage[2]. Our experiments were conducted on the 245 license plate images ,1470 characters in total, randomly captured in a city of China under uncontrolled circumstances.

The segmentation results on the images with typical degradations are presented in Fig. 3. The first two rows show the localized license images and the vertical projection histograms, and the third row illustrates the segmentation results in the rectified images in which the positions of the characters are indicated by vertical white lines. It can be seen that the proposed approach work well when the plate images exhibit connected characters (Fig. 3 (a)), severe corruption by stains (Fig. 3 (a) and (b)), irregular lighting (Fig. 3 (c)), physical distortion (Fig. 3 (d)) and lower contrast ((Fig. 3 (e)). In these cases, the projection histograms present such undesired peaks that would frustrate the traditional segmentation algorithms. In addition, our approach simultaneously recognizes the segmented character images correctly except for those in Fig. 3 (a) in which the stains notoriously fragment the edge maps of the character images. This would be tackled by upgrading the template matching recognizer in our model to the sophisticated ones.

Table 1 gives the recognition results compared with those obtained by the Hausdorrf-distance based algorithm and the shape context matching algorithm. The proposed approach shows the superior performance in terms of recognition rate

[2]http://www.vcipl.okstate.edu/∼ fanxin/downloads.htm.



(a) (b) (c) (d) (e)

Fig. 3. License images,projection histogram and segmentation results in various conditions.

Table 1. Recognition rate comparison

	Hausdorff	Shape context	Proposed method
Rate	84%	87%	92%

of characters. This improvement mainly owes to the incorporated combinational semantics that would correct the recognition errors. For example, our approach always output digits for the last three character images but the other two algorithms may mistake them as alphabetical letters.

5. CONCLUSION

In this paper, we pose the segmentation and recognition of license plate characters as the probabilistic estimation. Both the low-level and high-level constraints for segmentation and recognition are wrapped into a Markov network and the segmentation and recognition are achieved as the output of the BP inference algorithm. We performed the proposed algorithm on real-world license plate images captured in a city of China. The experiments show the promising results on combatting the degraded images where connected and distorted characters present.

We do not aim at developing heuristic techniques that may improve the performance in some pre-defined circumstance, instead we provide a new perspective for incorporating the constraints underlying previous techniques and formulate them into a graphical model. The sophisticated recognizers like SVM can be embedded in the model and other inference algorithms [11] than BP can be applied .

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