License Plate Localization With Efficient Markov Chain Monte Carlo

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ABSTRACT

This paper presents a novel efficient Markov Chain Monte Carlo (MCMC) method for License Plate (LP) localization. The proposed method formulates the LP image feature and prior knowledge into a unified Bayesian framework. Then the localization problem is derived as a maximizing-a-posterior (MAP) problem, which integrates color, edge and character feature of LP. We propose an efficient MCMC method, taking integrated local geometrical likelihood as proposal probability to make the inference feasible. The experimental results on real dataset are very promising in terms of detection rate and localization accuracy.

Categories and Subject Descriptors

H.4 [**Image Processing and Computer Vision**]: Miscellaneous

General Terms

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Keywords

license plate localization, feature likelihood, MCMC, proposal probability

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1. INTRODUCTION

With the number of cars growing dramatically in recent years, the need for traffic management is becoming more and more necessary and Intelligent Transportation System. The License Plate Recognition (LPR) system is one of the effective solutions. LP detection is the essential function of the LPR system.

Many LP detection algorithms have been proposed in the past. Most of these methods make use of LP features, like shape [1], background color [2], or characters [3]. And the biggest difference among these methods are feature representations as saliency-related features [4], MSER [5], CSER [6], wavelet [7] etc.. Some of them use rule based method to locate the LP with those features and other use machine learning based, like SVM [8], Adaboost [9], neural network [10] etc.. The precision of the resulting bounding box with ground truth, reported in [4] with 75% and [11] with 77%, has significant influence on performance of character segmentation and recognition in LPR system. However it is difficult to get precise bounding box of LP.

Motivated by the challenge, we propose a method using MCMC to get precise LP location. As a method for global optimization, MCMC sampling method is useful in a wide variety of application, such as tracking [12], image segmentation [13], shape matching [14], feature clustering [15] and so on. However, the promise of MCMC method has been shadowed by its shortcomings: Naive MCMC algorithms borrowed from statistic and physics are extremely inefficient-rejected by unacceptably long "burn-in" periods and incredibly slow "mixing" rates [16].

Inspired by [16, 17, 18], we improve the efficiency of MCMC by using local geometrical likelihood, which contains upper-left corner shape and lower-right corner shape, to compose the domain knowledge which greatly improve the convergence of MCMC, and obtain the global optimal solution with precise bounding box.

There are several advantages of the proposed method. First, the resulting bounding box, given by the maximum posterior probability of LP, is precise, which can improve the performance of segmentation and recognition method. Second, the convergence of MCMC is greatly improved by the proposal probability using domain knowledge. Third, background color can also be obtained by integrating the feature probability into the LP posterior probability. The paper is organized as follows: section 2 defines the problem and gives its formulation. The proposed efficient MCMC sampling is presented in section 3. Two experiments are conducted in section 4. Section 5 concludes this paper.

2. PROBLEM FORMULATION

Given an image, the problem of LP localization is to get its exact location parameterized by s. We define $p(s|I)$ as the posterior probability of a window parameteriezed by s, being a true positive. Hence, the localization problem is formulated as.

$$s^* = arg \max_{s \in \Theta} p(s|I) \tag{1}$$

Where Θ represents solution space, s is the parameter of LP, and I is the image. Following Bayes rule, the posterior probability is decomposed into a likelihood term and a prior term,

$$p(s|I) = \lambda p(I|s)\pi(s) \tag{2}$$

which will be described in detail later.

2.1 The solution space

Since LP is a rectangular region with different background colors, it can be represented by $s = \{x, y, w, h, c\}$. Where (x, y) is coordinate of upper-left corner of the rectangle, (w, h) is width and height of the rectangle, c represents the color of LP's background. The solution space is

$$\Theta = C \times R^4 \tag{3}$$

C is the enumerated color space of background. R^4 is the space for position and size.

2.2 Prior distribution

We assume the prior probability is made up of three independent prior probability: $p(x, y), p(w, h)$ and $p(c)$. As a common sense, $p(x, y)$ and $p(c)$ are uniform distributions. $p(w, h) \sim N(\mu_w, \mu_h, \sigma_w, \sigma_h)$, describes the prior probability of w and h. In the experiment, we choose $\mu_w = 120, \sigma_w = 20, \mu_h = 40, \sigma_h = 10$. So we get:

$$\pi(s) = p(x, y)p(w, h)p(c) \tag{4}$$

$$p(w, h) = \lambda e^{-\frac{(w-\mu_w)^2}{2\sigma_w^2} - \frac{(h-\mu_h)^2}{2\sigma_h^2}} \tag{5}$$

2.3 Likelihood

We decompose image likelihood into product of LP features likelihood, which contains background of color of LP, f_c, gradient around the candidate region, f_g, and characters texture, f_t. And these features likelihood are independent. Therefore, given a state $s = \{x, y, w, h, c\}$, we have following likelihood.

$$p(I|s) \propto p(f_c|s)p(f_g|s)p(f_t|s) \tag{6}$$

2.3.1 Background color likelihood

Background color likelihood can be presented by the area ratio of the color c. So $p(f_c|s)$ is formed like this (7):

$$p(f_c|s) = e^{-\lambda_c(1-\frac{N_c}{w \times h})} \tag{7}$$

N_c is the number of pixel with background color c in candidate region. For example pixels with $hue \in [200, 250]$ and $saturation \in [85, 255]$ belong to blue LP [2], λ_c is a constant. $\|c\| = 4$, since there are 4 types of LP with different background color: yellow, blue, white and black in China.

2.3.2 Gradient likelihood

We take gradient of four edges of a rectangular region as the gradient likelihood. With state s, the likelihood is

$$p(f_g|s) = \sum_{i=1}^{4} p(L_i|s) \tag{8}$$

$$p(L_i|s) = e^{-\lambda_g(1-g_i)} \tag{9}$$

$$g_i = \sum_{P \in L_i} \vec{g}_P \cdot \vec{v} / \sum_{P \in L_i} \|\vec{g}_P\| \tag{10}$$

L_i is the i^{th} side of candidate rectangle region, and $i = 1, 2, 3, 4$. λ_g is a constant. g_P is the gradient of pixel P, v is a vector: $(1, 0)$ or $(0, 1)$ depending on the L_i is vertical or horizontal.

2.3.3 Characters texture likelihood

The LP region contains massive character edge, whose center is near the center of the candidate region. Therefore

$$p(f_t|s) = e^{-\lambda_t(1-\frac{N_t}{w \times h})} \times e^{-\frac{(x_m-(x+w/2))^2}{2\sigma_x^2} - \frac{(y_m-(y+h/2))^2}{2\sigma_y^2}} \tag{11}$$

N_t is the quantity of the edge point with $\|g_P\| > T_t$. (x_m, y_m) is the center of edges of characters, $\sigma_x = 10, \sigma_y = 5$. By combining the prior and these likelihood, the posterior probability becomes:

$$p(s|I) = \lambda p(x, y)e^{-\frac{(w-\mu_w)^2}{2\sigma_w^2} - \frac{(h-\mu_h)^2}{2\sigma_h^2}} \times e^{-\lambda_c(1-\frac{N_c}{w \times h})} \sum_{i=1}^{4} p(L_i|s) \times e^{-\lambda_t(1-\frac{N_t}{w \times h})} e^{-\frac{(x_m-(x+w/2))^2}{2\sigma_x^2} - \frac{(y_m-(y+h/2))^2}{2\sigma_y^2}} \tag{12}$$

3. EFFICIENT MCMC SAMPLING

We want to find the s^* that maximizes the posterior probability $p(s|I)$. It's not easy to solve the problem with five dimensions. However, MCMC method provides a way to search for the maximum in such situation. The essence of MCMC is designing a Markov Chain to sample a probability distribution $p(s|I)$. At each iteration t, sample a candidate sate $s^{'}$ according to $q(s^{'}|s_{t-1})$. The state $s^{'}$ is accepted with the probability p:

$$p = \min(1, \frac{p(s^{'}|I)q(s_{t-1}|s^{'})}{p(s_{t-1}|I)q(s^{'}|s_{t-1})}) \tag{13}$$

If the state $s^{'}$ is accepted, $s_t = s^{'}$, otherwise $s_t = s_{t-1}$. The Markov Chain constructed by this way is a stationary distribution and equals to $p(s|I)$, without being influenced by proposal probability $q(s^{'}|s_{t-1})$ and initial state s_0. However a random proposal probability will lead to very slow convergence. The key point of our method is to design proper proposal probability which will make the Markov Chain traverse the solution space more efficiently.

3.1 Proposal probabilities

(a) (b)

Figure 1: (a)UL shape. (b)LR shape

For discriminativeness and convenience, we take $q(s) = q_{ul} * q_{lr}$. q_{ul} and q_{lr} are the likelihood of shape UL and LR respectively. The local geometrical shapes, upper-left corner (UL) and lower-right corner (LR), are constructed by a horizontal line and a vertical line, whose lengths are 80 and 20 respectively. Figure 1 shows the UL shape and LR shape.

$$q_{ul} = \sum_{P \in UL} \vec{g}_P \cdot \vec{v} / \sum_{P \in UL} \|\vec{g}_P\| \tag{14}$$

g_p and v have similar meaning in formulation (10). q_{lr} can be got in a similar way. Figure 2 shows that upper-left corner and lower-right corner have relatively higher q_{ul} and q_{lr} value respectively.

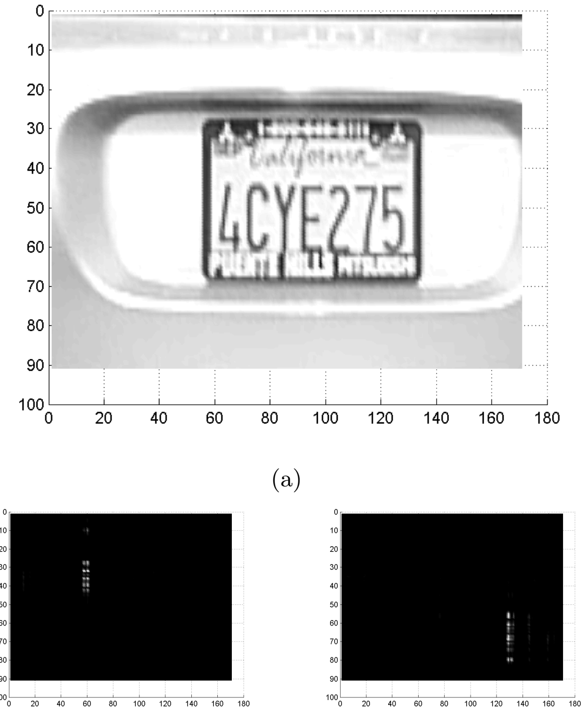
Given a state $\{x, y, w, h, c\}$, $q_{ul}(x, y) * q_{lr}(x+w, y+h)$ can be the proposal probability.

3.2 Markov Chain dynamics

Given a state $s_{t-1} = \{x, y, w, h, c\}$, these below Markov Chain dynamics are used to sample the proposal probability $q(s^{'}|s_{t-1})$. Randomly change $(x, y), (w, h), (x, y, w, h)$ or c, which are referred as Jump dynamics. Update the parameters (x, y) or (w, h) according to the gradient direction of q_{ul} and q_{dr}, which are referred as Diffusion dynamics. These guarantee the Markov Chain is ergodic and aperiodic.

4. EXPERIMENTAL RESULTS

We use method in [20] to get several candidate regions, which can dramatically reduce the area of ROI. Integral image technique [21] is also used to speed up the calculation of g_i and (x_m, y_m). In our experiments, the parameters are fixed as the followings: $\lambda_c = \lambda_g = \lambda_t = 1.0, \lambda = 1.2$. We test our method in our own dataset with 454 images, which are randomly taken from real world. We get 97.4% detection rate with average overlap accuracy 95% and the recognition rate for background color is 98%. Table 1 shows results compared with method in [19] and [11] by detection rate and average overlap on Caltech database. Figure 3 shows



(a)

(b) (c)

Figure 2: (a)original image. (b)upper-left corner (UL shape) probability. (c)lower-right corner (LR shape) probability

Table 1: Detection rate and overlap of different methods

	Detection rate	Average overlap
Method in [19]	83.7%	-
Method in [11]	94%	77%
Proposed method	96.8%	90%

some of the detection results. Bounding box got by using the proposed method is more precise than that got by using method in [11]. The experiment with the proposed approach shows the superior performance in terms of overlap between detection windows and ground truth. This will improve the performance of LP character segmentation and recognition.

We've also compared the convergence speed of original MCMC and the proposed method. Figure 4 shows maximum posterior probability of two different methods at each iteration. The maximum can be got in less than 400 iterations by the proposed method, while original MCMC is not convergent even after 1000 iterations. That shows our proposal probability can greatly improve the convergence of MCMC. A 1000-iteration run per image on the dataset used in the paper requires less than 0.5 seconds of CPU time on a Pentium dual 2.00G Hz PC.

5. CONCLUSION AND FUTURE WORK

In this paper we propose a novel method to solve the problem of LP localization, which is formulated as a Bayesian MAP problem. With properly designed proposal probabil-

(a)the proposed method (b)method in [11]

Figure 3: Some detection results on Caltech database

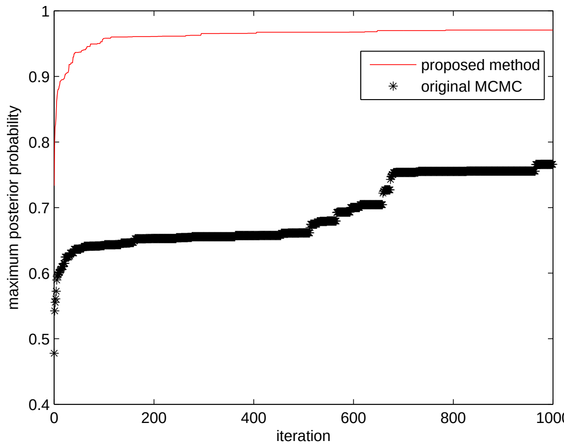


Figure 4: convergence of proposed method and original MCMC

ity, the convergence point can be got in much less time than naive MCMC method. The experiment shows the proposed method is very promising in terms of the overlap of bounding box with ground truth and efficiency in LP localization. These work described above can lead to significant performance improvement of characters segmentation and recognition, which we leave as our future work.

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