PROBABILISTIC MODELING AND FUSION FOR IMAGE FEATURE EXTRACTION WITH APPLICATIONS TO LICENSE PLATE DETECTION

Rami Al-Hmouz, Subhash Challa and Duc Vo
Networked Sensors Technologies Lab, University Of Technology Sydney, Sydney, Austrlia

Keywords: LPR, Plate Location, Extraction, Data Fusion.

Abstract: The paper proposes a novel feature fusion concept for object extraction. The image feature extraction process is modeled as a feature detection problem in noise. The geometric features are probabilistically modeled and detected under various detection thresholds. These detection results are then fused within the Bayesian framework to obtain the final features for further processing. Along with a probabilistic model, pixels voting algorithm is also tested through binary threshold variation. The performance of these approaches is compared with the traditional approaches of image feature extraction in the context of automatic license plate detection problem.

1 INTRODUCTION

Geometric features in the a image such as area, perimeter length etc, can determine the position of any object in the camera field of view. Weather condition and illumination have a significant impact on selecting the appropriate threshold and consequently on geometric features extraction. This paper proposes novel probabilistic fusion methods to improve such feature extraction.

We are specifically focused on methods of feature extraction that first convert the color or Gray Scale image into a binary image before feature detection/extraction. A binary image, is obtained from thresholding a Gray scale image; a threshold must be selected to label some intensity values as a white intensity and some as a black intensity. The selection of the threshold is critical to the quality of binary image and in terms of feature extraction. A new probabilistic fusion method for feature and subsequent object extraction is introduced in this paper and its potential in the context of license plate extraction application is demonstrated.

Automatic license plate recognition (ALPR) is a promising field of research, it has numerous application areas such as unattended parking lots (Sirithinaphong and Chamnongthai, 1998), security control of restricted areas (Yamaguchi et al., 1999), traffic law enforcement (Davieset et al., 1990) and automatic toll collection (Lotufo et al., 1990). ALPR techniques vary from one application to another according to their different working environments. In general, LPR algorithms are usually composed of three processing steps, namely, extraction of the region of the license plate, segmentation of characters from the plate region, and recognition of each character.

Extracted License plate region is the most important and challenging step of the plate recognition, because it is the first step and the next steps of LPR depend on it. Generally, there are three method of extracting the plate from an image:

1. Plate features: The colored image is converted into a gray level image in which a threshold is selected to obtain the image in a black and white format. A rectangular region with plate features is the candidate region which needs to be located. A good contrast of image pixels and a carefully selected threshold are necessary in order to the plate to be appeared in the image in standard plate features such features include shape symmetry (Kim and Chien, 2001), height to width ratio (Naito et al., 2000), color (Kim et al., 1996), area and pixels density.

Al-Hmouz R., Challa S. and Vo D. (2007).
PROBABILISTIC MODELING AND FUSION FOR IMAGE FEATURE EXTRACTION WITH APPLICATIONS TO LICENSE PLATE DETECTION.
In *Proceedings of the Second International Conference on Computer Vision Theory and Applications - IFP/IA*, pages 398-403

2. Edge detection(Parker and Federl, 1996): the process depends on either the edges of the plate or the edges of the characters. Any edge detection technique can be used to locate the edges,as a rule,the plate and characters have many vertical edges. A threshold should be chosen carefully for various illuminants and weather conditions.

3. Signature analysis: the plate region is classified based on plate signature. The signature could be a big variation in the pixels brightness in some rows of the input image (Barroso et al., 1997) or it could be any text seen in the image (Dlagnekov, 2005).

All of the previous methods work perfectly in the absence of uncertainties. Noise is produced because of:

- Various colors for the characters and plate background.
- Weather condition and different illuminations.
- Non character symbols and dirt on license plate
- Non uniform lighting across the plate.
- Image processing noise.

Combining multiple classifiers has been long pursued for improving the accuracy of single classifiers (Rahman and Fairhurst, 2003). A classifier fusion-based detection algorithm was introduced by (Huang and Guo, 2003) to extract the optimal features form the candidate plate region.

In this paper, a novel technique of object extraction based on modeling of geometric features is proposed. Geometric features are model as random variables and the fusion result of features will be a measure of detection and extraction of an object in the seen image. Multiple binary images for a Gray scale image are obtained form multiple thresholds, Bayes' rule is used to update the posterior under the assumption of normal distribution of all uncertainties. Also, a deterministic method of object extraction based on geometric features is presented,pixels vote for the area that appear the most in the same context of threshold variation. Both methods are tested on license plate extraction application under various illumination conditions.

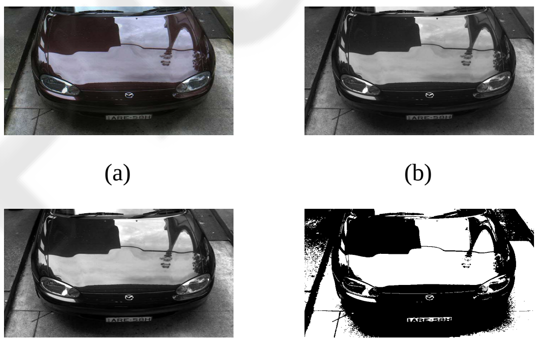
The rest of the paper is organized as follows: section 2 Plate extraction algorithm, section 3 explains Plate extraction model Algorithm, section 4 shows the experimental results and finally section 5 concludes the paper.

2 PLATE EXTRACTION ALGORITHM

The first step in the LPR system is acquiring frames from a digital camera. Light illumination and the quality of the selected frame are having an effect on all over LPR system and especially on the first part of plate extraction; however some image processing techniques can be used to estimate the illuminate (Finlayson et al.,2001) or enhance image equality (Rajaram et al., 2006) before the image got passed to the next module of plate extraction.

2.1 Image Processing

Initially, the colored input image is converted into a Gray scale image, then the Gray image is normalized to increase the contrast between the plate back ground and other areas around it as shown in Figure 1. A selected threshold is chosen to convert the image into a binary format, OTSU technique (Otsu, 1979) can be used to find the optimal threshold. However, Thresholding the image could be ended up with unconnected plate region or totally missing the plate region.



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

Figure 1: Image conversion (a)Original. (b)Grey scale. (c)Normalization gray. (d)Binary.

Multiple thresholds are used to convert the image into black and white in order to guarantee that the plate region will be appeared at least once in the view, also plates come with various colors, it is hard for the plate region to appear under different illuminants, therefore varying the thresholds will help the plate to appear as a connected region at least once in the binary images.

2.2 Plate Extraction

Most plates in New South Wales (NSW) Australia come in a rectangular shape with a dark black frame around them which help to distinguish the plate area as seen in Figure 2.

Figure 2: NSW plate types.

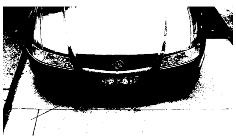
The most common features that identify the plate are:

1. length/width ratio (u).
2. back ground area (a).
3. character/plate area density (d).

The binary image consists of black and white regions,the white regions appear as connected areas among the black regions. The nominated plate is among the white areas if the threshold has been chosen carefully. Most studies which use this method examine whether the connected region features fall in the standard license plate features or not, then again, noise will affect on those features as well as regions having the same plate features such as the front lights have an affect on selecting the right plate as can be seen in Figure 3.

(a)

(b)



(c)

(d)

Figure 3: Thresholding image (a)Original. (b)t1. (c)t2. (d)t3.

The probability of each connected region that can be selected as a plate region under the assumption that features are under the influence of normally distributed noise, is calculated by using a three-degree Gaussian distribution:

$$p(z) = \frac{1}{(2\pi)^{1/2}(detV)^{1/2}} exp\left[-\frac{1}{2}(z-s)^T V^{-1}(z-s)\right] \quad (1)$$

where:

$$z = \begin{bmatrix} u \\ a \\ d \end{bmatrix}$$

is vector of random variables (measurements of region features).

$$s = \begin{bmatrix} m_u \\ m_a \\ m_d \end{bmatrix}$$

is the average standard plate features,

$$m = \frac{1}{N}\sum_{j=1}^{N} \frac{Max(i)_j + Min(i)_j}{2}, ..N = 100, i = u,a,d.$$

N is number of plates used to find the mean of plate area and

$$V = \begin{bmatrix} \sigma_u^2 & 0 & 0 \\ 0 & \sigma_a^2 & 0 \\ 0 & 0 & \sigma_d^2 \end{bmatrix}$$

is the Variance,

$$\sigma_i^2 = \frac{1}{N}\sum_{i=1}^{N}(i-m_i)^2 ...i = u,a,d.$$

The region that have the highest probability will be selected as the candidate plate region,the selected region features are almost similar to the standard plate features. Vector z can be expand to include other region features such as the orientation and perimeter of the connected regions.

3 PLATE EXTRACTION MODEL ALGORITHM

Let $R_1, R_2, ..., R_n$ be the connected regions and $t_1, t_2, ..., t_m$ be the thresholds been used to convert the image into black and white then:

$$p(R_n/t_m) = \frac{1}{(2\pi)^{1/2}(detV)^{1/2}} exp\left[-\frac{1}{2}(R_n-s)^T V^{-1}(R_n-s)\right] \quad (2)$$

The probability of the pixel v_{ij} is

$$P(v_{ij}/t_m) = \begin{cases} p(R_n/t_m)/\Delta & if v_{ij} \in R_n \\ \frac{Min(p(R_n/t_m))}{2}/\Delta & otherwise \end{cases} \quad (3)$$

Δ is the normalization all over the image pixels.

The probabilities of the regions are assigned to the pixels that belong to the same regions, for example of a region R_1 has a probability 0.1 then all pixels inside this region will have the same probability and the other pixels who do not have regions will have a small probability which is less than any connected region probability $Min(p(R_n/t_m))$, this small probability is assigned to these pixel in order avoid multiplication by zero. The highest pixels probabilities locate the license plate region and from the indices the plate can be simply extracted.

The plate region could be defected because of the noise problem, threshold t_1 will produce $P(v_{ij}/t_1)$, correspondingly threshold t_2 informs with another $P(v_{ij}/t_2)$, it is like a new sensor inform with a new data. The most probable plate region will appear several times when using several thresholds. The updated posterior $P(v_{ij}/t_1,t_2)$ can be calculated using Bayes' rule:

$$P(v_{ij}/t_1,t_2) = \frac{P(t_1/v_{ij},t_2)\cdot P(v_{ij}/t_2)}{p(t_1,t_2)} \tag{4}$$

The noise pixels are identical independently distributed,then

$$P(v_{ij}/t_1,t_2) = \frac{P(v_{ij}/t_1)P(v_{ij}/t_2)}{\Delta} \tag{5}$$

Recursive updating is simplified assuming conditional independence of the measurements (Pearl, 1998) which implies

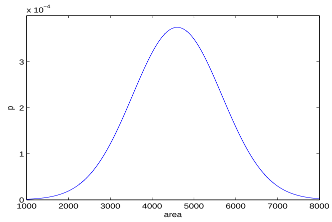
$$P(v_{ij}/t_1,t_2,....,t_n) = \Delta\prod_{\gamma=1}^{n} P(v_{ij}/t_\gamma) \tag{6}$$

Other methods of plate extraction for example edge detection technique can be used to inform with another connected regions, Instead of converting the image into a binary format, the edge is detected in order to form connected regions and then the connected region probabilities are calculated as previous method using equation 1 and the update using equation 6.

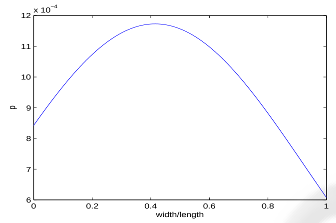
4 EXPERIMENTAL RESULTS

The algorithm has been tested on 500 colored images. All images tested on 480*640 pixels obtained form Mobitx (Mobotix) camera which located in a car park, the image were taken from different colors and sizes of NSW plates. The plate region features statistics are shown in Figure 4.

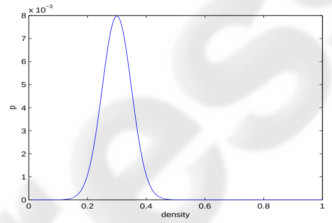
The algorithm successfully locates the license plate in 98%. Using various thresholds and updating the posterior boosts the result accuracy. Figure



(a)



(b)



(c)

Figure 4: Plate features distributions (a)Area. (b)width/length. (c)Density.

5 shows the binary images of different threshold values, at a certain threshold there would be several areas that could be nominated as the candidate plate. Once updating the results with each other, some area will be killed and disappear and others will be boosted and come into view. When comparing this results with traditional method of plate extraction using the threshold $t4$, the method will fail to extract the plate region,becuase the plate area region doesnt form under that particular thershold value. The regions probabilities are assigned to thier pixels as seen in Figure 6, after udating the posterior $P(v_{ij})$, The pixels with highest probabilities will be selected as the candidate plate.

In order for the plate region to be appeared more than any region in the image, the thresholds should be in the range of the optimal threshold. If this was not the case, other regions will appear more and their pixel probabilities will be higher than the plate region pixels probabilities, as a result, another region will be picked up as a candidate region. In most cases, thresholds in the range between 0.15 to .45 in 8 bit

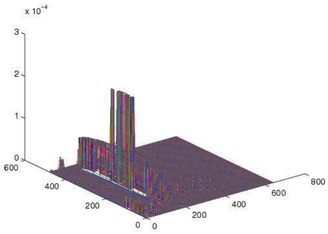
(a)

(b)

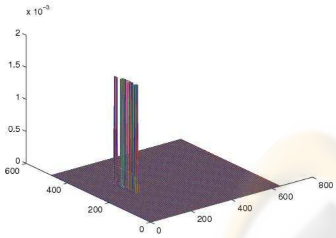
(c)

(d)

Figure 5: Binary images (a)t1. (b)t2. (c)t3. (b)t4.



(a)



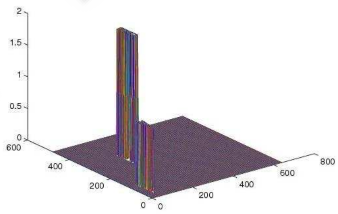
(b)

Figure 6: Posterior pixels probabilities (a)$P(v/t_1,t_2)$. (b)$P(v/t_1,t_2t_3,t_4)$.

gray-level will be sufficient for plate region to appear at least once. Moreover, in some cases when the probability of the plate region is not high enough, the normalization all over the image pixels will kill this probabilities and become almost as other pixels probabilities. Yet, instead of assigning probabilities to the plate pixels and fuse the result using Bayes' rule, a deterministic method can be used to locate the plate, and fusion is achieved through pixels voting. For each threshold, the plate area is tested using the traditional method of plate extraction using plate feature and the candidate plate region will vote for the most seen pixels, the pixels with highest votes form the different thresholds will be picked up as the plate region. In Figure 7, two regions appear to be a candidate region for the plate but one of them has more votes than the other, the region with more vote is the candidate plate region.

The miss located number plates are all of that the connected regions of the plate area which do not take the plate shape because of indistinguishable frame around the plate; the area of a connected plate region might not be formed under any threshold value. In addition, when the plate back ground color is almost the same the vehicle's color in which the plate regions could not be formed. Therefore, using another method to locate the license plate is essential to locate the plate correctly and yet the results from both methods can be fused to enhance the performance for these special cases, as well as for the case when the frame is clearly visible around the plate.

(a)



(b)

Figure 7: (a)Original. (b)Pixels voting.

Both algorithms have high accuracy of plate extraction due to the variation of the threshold values which allow the plate to show up in the binary image.Furthermore, more tests can be carried out on the plate region to confirm the previous tests. The number of character can be counted after the plate is extracted, also whether if they are in the line or not. If this test fails, the next highest probability/vote region will be tested. If the test still fails, then different threshold or another algorithm should be examined.

5 CONCLUSION AND FUTURE WORK

In this paper, new robust techniques of license plate detection and extraction have been presented. Multiple thresholds are used to convert the image into binary images, each binary image acts as a sensor that informs with new data, and results from binary images are fused using a probabilistic approach and a deterministic approach. In the probabilistic approach, the plate geometric features are modeled as random variables which are normally distributed, the probability of connected regions is calculated through fusion of region features. In the deterministic approach, the candidate plate region is extracted for every threshold, the pixels which are appeared the most will vote for the plate region. Geometric features are tested for both methods, results showed the efficiency for both methods and how they outperform traditional methods of plate extraction.

For future work, other methods of plate extraction will be examined, an appropriate probabilistic model needed to be investigated in order both results can be fused together throughout updating the posterior with new data.

REFERENCES

Barroso, J. Bulas-Cruz, J. and Dagless, E. L. (1997). Real Time Number Plate Reading. In *4th IFAC Workshop on Algorithms and Architectures for Real-time Control, Portugal*.

Davies,P. Emmott, N. and Ayland, N. (1990). License plate recognition technology for toll violation enforcement In *Inst. Elect. Eng. Colloquium Image Analysis for Transport Applications, pp. 7/1-7/5*.

Dlagnekov, L (2005). Video-based Car Surveillance: License Plate, Make, and Model Recognition. A Masters of Science in Computer Science thesis. UNIVERSITY OF CALIFORNIA, SAN DIEGO.

Finlayson, G. Hordley, S. and Hubel, P. (2001). Color by correlation: A simple,unifying framework for color constancy. In *IEEE Transactions on Pattern Analysis and Machine Intelligence, 23(11):12091221*.

Huang, Z. and Guo, Y . (2003). Classifier Fusion Based Vehicle License Plate Detection Algorithm. In *proceedings of the Second International Conference on Machine Learning and Cybernetics , pp. 2984-2989*.

Kim, D. S. and Chien,S. I. (2001). Automatic car license plate extraction using modified generalized symmetry transform and image warping. In *Proc. IEEE Int. Symp. Industrial Electronics, vol. 3, pp. 2022-2027*.

Kim,S. K. Kim,D. W. and Kim, H. J.(1996). A recognition of vehicle license plate using a genetic algorithm based segmentation. In *Proc. Int. Conf. Image Processing, vol. 2, pp. 661-664*.

Lotufo, R. A. Morgan, A.D. and Johnson,A. S. (1990). Automatic numberplate recognition. In *Inst. Elect. Eng. Colloquium on Image Analysis for Transport Applications, pp. 6/1-6/6*.

Mobotix. Retrieved November 10, 2006, from. *http://www.mobotix-camera.com/*.

Naito,T. Tsukada,T. Yamada,K. Kozuka,K. and Yamamoto, S. (2000). Robust license-plate recognition method for passing vehicles under outside environment. In *IEEE Trans. Veh. Technol., vol. 49, pp. 2309-2319*.

Otsu, N. (1979). A threshold selection method from gray level histograms. In *IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-9, pp. 62-66*.

Parker, J. R. and Federl, P. (1996). An approach to license plate recognition. In *Computer Science Technical reports, University of Calgary, Alberta Canada, Vol. 591-11*.

Pearl, J (1998). *Probabilistic Reasoning in Intelligent Systems*. Morgan Kaufmann,San Francisco, CA,USA.

Rahman,A.F.R. and Fairhurst,M.C. (2003). Multiple classifier decision combination strategies for character recognition: a review. In *Int. J. Document Analysis and Recognition, 5(4): 166-194*.

Rajaram, S. Gupta M.S. Petrovic, N.,3 and Huang, T.S. (2006). Learning-Based Nonparametric Image Super-Resolution. In *EURASIP Journal on Applied Signal Processing Volume 2006, Article ID 51306, Pages 111 DOI 10.1155/ASP/2006/5130*.

Sirithinaphong, T and Chamnongthai,K. (1998). The recognition of car license plate for automatic parking system. In *5th Int. Symp, Signal Processing and its Applications, pp. 455-457*.

Yamaguchi, K. Nagaya, Y. Ueda, K. Nemoto,H. and Nakagawa,M. (1999). A method for identifying specific vehicles using template matching. In *Proc. IEEE Int. Conf. Intelligent Transportation Systems,pp.8-13*.