

Design of a Recognizing System for Vehicle's License Plates with English Characters

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Abstract

In recent years, video detection systems have been implemented in various infrastructures such as airport, public transportation, power generation system, water dam and so on. Recognizing moving objects in video sequence is an important problem in computer vision, with applications in several fields, such as video surveillance and target tracking. Segmentation and tracking of multiple vehicles in crowded situations is made difficult by inter-object occlusion.

In the system described in this paper, the mean shift algorithm is firstly used to filter and segment a color vehicle image in order to get candidate regions. These candidate regions are then analyzed and classified in order to decide whether a candidate region contains a license plate or not. And then some characters in the license plate is recognized by using the fuzzy ARTMAP neural network, which is a relatively new architecture of the neural network family and has the capability to learn incrementally unlike the conventional BP network. We finally design a license plate recognition system using the mean shift algorithm and fuzzy ARTMAP neural network and show its performance via some computer simulations.

Key Words : License plate recognition, Image processing, Mean shift algorithm, Fuzzy ARTMAP, Neural Network

1. Introduction

During the past few years, intelligent transportation systems (ITSs) have had a broad impact in people's lives as they have improved transportation safety and mobility and enhanced productivity through the use of advanced technologies. These systems are divided into intelligent infrastructure systems and intelligent vehicle systems. In this paper, a computer vision and character recognition algorithm for a license plate recognition (LPR) is presented. The system presented is suitable as a core component for use in intelligent infrastructures like electronic payment (toll payment, parking fee payment) systems, and freeway and arterial management systems for traffic surveillance. Moreover, as increased security awareness has made the need for vehicle based authentication technologies extremely significant, the proposed system may be employed as an access control system for monitoring of unauthorized vehicles entering private areas.

The license plate remains as the principal vehicle identifier despite the fact that it can be deliberately altered in situations of fraud or replaced (e.g. with a stolen plate). Therefore, ITSs rely heavily on robust LPR systems. The main job is to analyze images obtained from the camera, according to an image processing technique, and then recognize some characters in the plate. Specifically, the contributions are as follows:

- 1) a discontinuity preserving smoothing technique named mean shift algorithm used for faster detection of regions of interest (RoI);
- 2) an algorithmic sequence called Fuzzy ARTMAP is used to recognize some characters.

There are three stages in the recognition process: license plate detection, character extraction and character recognition. They will be presented in detail in the next part.

2. Related Works

It is known that a license plate is a pattern composed of several characters that have high distinctive intensities from their background. The high contrast area can be used as a key feature to detect the desired license plate region. In the following, we will describe a mean shift based method to extract the high contrast area and detect the desired license plate area. We then describe how to utilize Fuzzy ARTMAP to recognize some characters in the extracted area. A flowchart of the proposed license plate detection algorithm is shown in Fig.1.

The first stage is to determine a candidate area from real vehicle images where license plate could exist. This stage deals with image acquisition and the pre-processing operation which removes the noise. The filtering operation of this stage brings the image to an appropriate format for the identification stage. To detect the character region of the license plate, the mean shift algorithm and intensity de-

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rivatives are used. The mean shift algorithm is a non-parametric clustering technique which does not require prior knowledge of the number of clusters, and does not constrain the shape of the clusters.

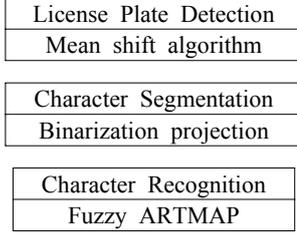


Fig. 1 A three stage approach for a license plate recognition

The second stage is a segmentation of extracted license plate. This includes character extraction. In LPR system, a lot of prior information can be utilized such as the size of the license plate, the size of the characters, and the position of the characters on the license plate. In this paper, we use the information such as contour, shape and disposition to locate the characters. We then use the binarization method to process the extracted characters to provide a stable character feature.

The last stage is a character recognition which is one of the core part of our research. This identification stage deals with the optical recognition of the English and numeric characters in the digital image, and the identification of the vehicle number. Actually, it is an OCR system. An excellent survey on OCR is given by Carpenter et al. [7]. In our application, we need to recognize the printed characters which is easier than handwritten character recognition. In this paper, we introduce the grid feature and artificial neural network to perform the OCR test.

3. Design of License Plate Recognition System

The LPR sequence, which is proposed in this paper, consists of two distinct parts. The first one deals with the detection of the RoI, i.e., the license plate. The second part includes operations for the successful segmentation of the license plate characters along with an artificial neural network, which performs the OCR task.

3.1 Part 1: License Plate Segmentation

This part consists of preprocessing in order to detect the RoI in ambient illumination conditions. The preprocessing component consists of four tasks: implementation of the mean shift filtering method, delineation of the cluster, elimination of spatial regions smaller than M pixels, and extraction of the rectangularity and aspect ratio. The discontinuity preserving smoothing of the mean shift algorithm is indicated in Table I.

An image is typically represented as a two-dimensional lattice of p -dimensional vectors. The space of the lattice is

known as the spatial domain, while gray level, color, or spectral information is represented in the range domain. For both domains, Euclidean metric is assumed. When the location and range vectors are concatenated in the joint spatial-range domain of dimension $d=p+2$, their different nature has to be compensated by proper normalization. Thus the multi-variate kernel is defined as the product of two radially symmetric kernels and the Euclidean metric allows a single bandwidth parameter for each domain

$$K_{h_s, h_r}(x) = \frac{C}{h_s^2 h_r^p} k\left(\left\|\frac{x^s}{h_s}\right\|^2\right) k\left(\left\|\frac{x^r}{h_r}\right\|^2\right) \quad (1)$$

where x^s is the spatial variable, x^r is the range variable of a feature vector, $k(x)$ is the common profile used in both of the two domains, and C is the corresponding normalization constant.

In the joint spatial-range domain we used mean shift filtering, each data point is associated to a point of convergence which represents the local mode of the density in the d -dimensional space. Smoothing through replacing the pixel in the center of a window by the average of the pixels in the window blurs the image indiscriminately and removes not only the noise but also salient information. Discontinuity preserving smoothing techniques, on the other hand, reduces the amount of smoothing near abrupt change in the structure adaptively. The procedure continues until all pixels in the image are scanned.

The license plate segmentation operation is implemented on the mean shift filtered images. The original input image is firstly normalized with a normal kernel function, where the bandwidths in the spatial domain and the range domain are denoted as h_s and h_r , respectively. Let x_i and z_i , $j = 1, 2, \dots, n$, be the d -dimensional input and filtered image pixels in the joint spatial-range domain, respectively.

Since this process takes into account both the spatial and range information of the image simultaneously, it can achieve a high quality and discontinuity preserving spatial filtering.

After the candidate regions are obtained by applying mean shift filtering, features of each region are to be extracted in order to differentiate the license plate regions from others correctly. Various features have been utilized for this purpose. Such features include the size of the region, the width and the height of the region, the orientation of the characters, edge features, and the position of the region. Some features, however, can deal with images captured under very specific environmental conditions.

The license plate has a rectangular shape with a predetermined length to width ratio on each kind of vehicle. Due to the viewing angle and uneven or curvy road surfaces, however, license plate images taken from a vehicle image are usually no longer a standard rectangular shape. Under limited distortion, however, license plates in vehicle images can still be viewed as approximately as rectangular shape with a certain aspect ratio. This is the most important shape feature of license plates.

Table I. Discontinuity Preserving Smoothing

Input: image I
1. Run the mean shift filtering procedure for x_j and get filter image pixels z_j , where $j=1, 2, \dots, n$, as (1) Initialize $k=1$ and $y_{i,k} = x_j$ (2) Compute $y_{i,k+1} = \frac{\sum_{i=1}^n x_i g(\ \frac{x-x_i}{h} \ ^2)}{\sum_{i=1}^n g(\ \frac{x-x_i}{h} \ ^2)}$, until it converges, and $y = y_{i,c}$. Where $g(x) = -k_N'(x) = \begin{cases} c \ x\ < 1 \\ 0 \text{ otherwise} \end{cases}$ (3) Assign $z_j = (x_i^s, y_{i,c}^r)$. The superscripts s and r denote the spatial and range components of a vector, respectively. The assignment specifies that the filtered data at the spatial x_i^s will have the range component of the point of convergence $y_{i,c}^r$. 2. Delineate the clusters $\{C_p\}_{p=1,2,\dots,m}$ in the joint domain by grouping together all z_j which are closer than h_s in the spatial domain and h_r in the range domain. 3. Assign $L_j = \{p z_j \in C_p\}$ for each $j=1, 2, \dots, n$, 4. Eliminate spatial regions that are smaller than M pixels

A quick and straightforward method is used to detect the edge of the object region to get its minimum enclosing rectangle (MER). With this method, an edge of RoI is a transition from background to object or vice versa. But for an image that contains a license plate may also include the dynamo and fore-baffle etc, which have very strong horizontal edges. We can see that a vertical edge detector is better than a horizontal edge detector in suppressing horizontal noise.

$$\begin{aligned}
 g_H &= |[f(i-1, j-1) + 2f(i-1, j) + f(i-1, j+1)] \\
 &\quad - [f(i+1, j-1) + 2f(i+1, j) + f(i+1, j+1)]| \\
 g_V &= |[f(i-1, j-1) + 2f(i, j-1) + f(i+1, j-1)] \\
 &\quad - [f(i-1, j+1) + 2f(i, j+1) + f(i+1, j+1)]|
 \end{aligned} \tag{2}$$

Where $f(i, j)$ represents the gray image of the input image after smoothing and normalization, $g_H(i, j)$ and $g_V(i, j)$ represents the horizontal edge map and vertical edge map, respectively.

The aspect ratio is defined as the ratio of the width to the height of the region's MER. Since the MER of the object region can be computed via rotating the region in the previous section, the dimension of the object's MER can be taken as the width and the height of the region. This ratio is defined by

$$\text{ratio} = \frac{c_{\max} - c_{\min} + 1}{r_{\max} - r_{\min} + 1} \tag{3}$$

where c and r indicates column and row, respectively. The orientation of the object is defined by

$$\tan(2\theta_i) = 2 \frac{\sum_{r=0}^{N-1} \sum_{c=0}^{N-1} rc I_i(r, c)}{\sum_{r=0}^{N-1} \sum_{c=0}^{N-1} r^2 I_i(r, c) - \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} c^2 I_i(r, c)} \tag{4}$$

Those candidate regions whose measurements fulfill the criteria orientation $< 35^\circ$, $2 < \text{aspect ratio} < 6$, are considered as candidate plate regions.

After applying the above three features to filter the segmented regions, many non-license plate regions can be removed. However, many candidate regions are still left, which have similar rectangularity and aspect ratio features as the license plate regions do, such as the head lights. The edge density is measured in a region R by averaging the intensities of all edge pixels within the region as

$$D_R = \frac{1}{N_R} \sum_{m,n \in R} E(m, n) \tag{5}$$

where $E(i, j)$ represents the edge magnitude at location (i, j) , and N_R is the number of pixels in region R .

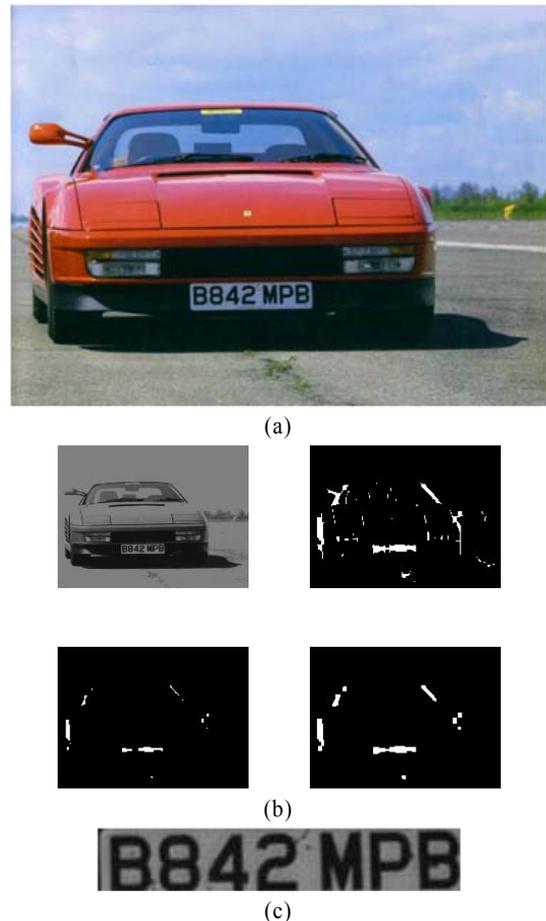


Fig. 2 Steps for license plate segmentation: (a) Initial image. (b) Results of mean shift algorithm and edge detection. (c) Detected plate region.

3.2 Part 2: License Plate Processing

This part consists of the preprocessing and forward step.

Preprocessing isolates the characters in the license plate image. And the forward step sends those characters to the Fuzzy ARTMAP neural network for identification.

Following the inversion of the resulting image and object labeling, the orientations and heights of connected components (objects) are then calculated. The components whose measurements do not fulfill specific rules (orientation $> 75^\circ$ and height > 32 pixels) are deleted. The remaining objects are then forwarded to Fuzzy ARTMAP after a well defined preparation process. And it includes character segmentation calculating the standard deviation of columns and rows, and the transformation of each character to the size of the input vector of the Fuzzy ARTMAP. Fig. 3 presents an example of license plate processing with the proposed algorithm.

B842 MPB

Fig. 3 Successful segmentation of the character part

3.3 Part 3: Character Recognition

After the Character Segmentation is finished, the next step is to recognize some characters. A combination of neural and fuzzy techniques (Fuzzy ARTMAP Neural Network) is used to guarantee a very low error rate at an acceptable recognition rate. It is widely applied in practice, which will be introduced in the following paragraphs.

ARTMAP (Adaptive Resonance Theory - Mapping) is a class of neural networks that can perform incremental supervised learning. It also performs multi-dimensional mapping in response to binary input vectors presented arbitrarily. The Fuzzy ARTMAP extends the ARTMAP by integrating fuzzy logic into the system, which allows it to accept input vector values between 0 and 1.

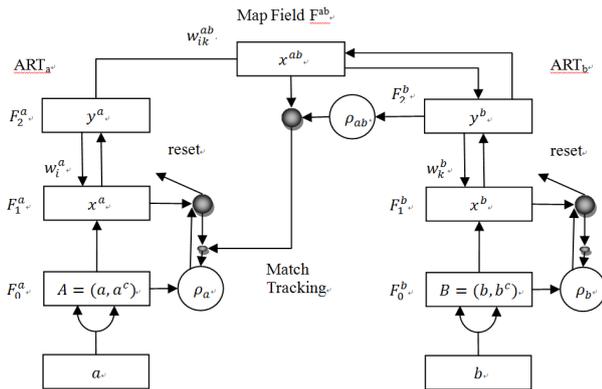


Fig. 4 Fuzzy ARTMAP Architecture

Fuzzy ARTMAP (Fig.4) consists of two fuzzy ART modules (ART_a and ART_b). The parameters of these networks are designated by the subscripts a and b, respectively. The fuzzy ART algorithm is summarized in Table II.

Table II. Summary of Fuzzy ART Algorithm

1. ART Field Activity Vector: The ART complement coding pre-processor transforms the M vector a into the $2M$ vector $A = (a, a^c)$ at the ART field F_0 . A is the input vector to the ART_a field F_1 .
2. Initial Weight Vectors: $w_j = 1$. $w_j = (w_{j1}, w_{j2}, \dots, w_{j,2M_a})$ denotes the F_2 output vector.
3. Category Choice: For each input I and F_2 node j , the choice function, $T_j = \frac{|I \wedge w_j|}{\alpha + |w_j|}$, and the category choice is indexed by J , where $T_J = \max\{T_j : j = 1 \dots N\}$. When the J th category is chosen, $y_J = 1$; and $y_j = 0$ for $j \neq J$.
4. Activity Vector x :

$$x = \begin{cases} I & F_2 \text{ isn't active} \\ I \wedge w_j & \text{Jth node of } F_2 \text{ node is chosen} \end{cases}$$
5. Resonance or Reset: If the match function, $\frac{|I \wedge w_j|}{|I|} \geq \rho$, resonance occurs. Then the learning begins. Else T_j is set to 0 and a new index J is chosen by category function. The search process continues until J satisfies.
6. Learning: After ending of the searches, the weight vector w_j is updated by $w_j^{\text{new}} = \beta(I \wedge w_j^{\text{old}}) + (1 - \beta)w_j^{\text{old}}$.

The two Fuzzy ARTs are interconnected by a series of connections between F_2 layers of ART_a and ART_b. These connections form what is called the *map field* F_{ab} . The map field is used to form predictive associations between categories and to realize the match tracking rule, whereby the vigilance parameter of ART_a increases in response to a predictive mismatch at ART_b.

The input to ART_a and ART_b are in complement code form, which is necessary for the successful operation of fuzzy ARTMAP. For ART_a, if input is $I_o = (a_1, \dots, a_{M_a})$, then

$$I = (a, a^c) = (a_1, \dots, a_{M_a}, a_1^c, \dots, a_{M_a}^c) \quad (6)$$

where

$$a_i^c = 1 - a_i \quad 1 \leq i \leq M_a.$$

The F_1^a activity vector is denoted by $x^a = (x_1^a, \dots, x_{2M_a}^a)$ and the F_2^a activity vector with N_a number of categories is denoted by $y^a = (y_1^a, \dots, y_{N_a}^a)$. M_a and N_a are arbitrary. For ART_b, $O_o = (b_1, \dots, b_{M_b})$, $O = (b, b^c)$. The F_1^b activity vector is denoted by $x^b = (x_1^b, \dots, x_{2M_b}^b)$ and the F_2^b activity vector with N_b number of categories is denoted by $y^b = (y_1^b, \dots, y_{N_b}^b)$. M_b and N_b are also arbitrary. For the inter-ART modules, the map field F_{ab} output vector is denoted by $x^{ab} = (x_1^{ab}, \dots, x_{N_b}^{ab})$, and let $w^{ab} = (w_{j1}^{ab}, \dots, w_{jN_b}^{ab})$ denote the weight vector from the j -th F_2^b node to F_{ab} . Vectors $x^a, y^a, x^b, y^b, x^{ab}$ are initialized to zero between input presentations.

The inter-ART module F_{ab} is activated whenever any of the ART_a or ART_b categories is active. The F_{ab} output

vector x^{ab} obeys

$$x^{ab} = \begin{cases} y^b \wedge w_J^{ab} & \text{the ART}_a \text{ and ART}_b \text{ is active} \\ w_J^{ab} & \text{ART}_a \text{ is active, ART}_b \text{ isn't active} \\ y^b & \text{ART}_a \text{ isn't active, and ART}_b \text{ is active} \\ 0 & \text{the ART}_a \text{ and ART}_b \text{ isn't active} \end{cases} \quad (7)$$

During the learning phase, the input vector I_o is presented to ART_a and the desired output vector O_o is presented to ART_b . The ART_a vigilance parameter ρ_a , equals the baseline vigilance, $\bar{\rho}_a$ at the beginning of every input presentation. When Fuzzy ARTMAP receives an input/output pair (I_o/O_o), ART_a chooses the J _th node of F_2^a and ART_b chooses the K _th node of F_2^b . When both ART_a and ART_b are active and $x^{ab} \neq 0$, then the input/output pairs are associated with the equation:

$$w_{jk}^{ab} = \begin{cases} 1 & j = J \text{ and } k = K \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

The ART_a and ART_b modules classify the input and desired output vector into categories, then the map field (inter-ART module) makes associations from the ART_a category to the ART_b category.

If $x^{ab} = 0$, then there is a mismatch. The Inter-ART module triggers a match tracking mechanism, which increases ρ_a , by a minimum value. And it forces the ART_a module to search for another category suitable to be associated with the desired output vector. ρ_a is then set back to the baseline vigilance parameter, $\bar{\rho}$, for every step of learning trial.

4. Simulation Results

To evaluate the efficiency, our method has been tested using MATLAB 2008 over colour images, acquired by a digital camera for real scenes. The test image has been acquired from the front as well as from the rear of vehicles under various illumination and weather conditions (such as sunny, cloudy, daytime, and night time).

There are several types of license plates for the identification of the vehicle. They are not the same in their shape, size, character type, and etc. They even include some background images of tree, building, or etc. These license plates are used to test the performance of the proposed algorithm.

A lot of templates was needed in the proposed system which requires substantial time to make the classifier, but it is essential. Some of the obtained images from the digital camera and binarization results of the license plate are shown in Fig. 5.

In the part of character recognition, the inputs of Fuzzy ARTMAP algorithm are the images of numbers and letters on vehicle license plates. The testing set has 300 characters, around 85% of the characters have better quality, and the others are all degenerate to different degree.



(a)



(b)



(c)



(d)

Fig. 5 Some License Plates: (a) and (c): Initial images. (b) and (d): Binarization results

Based on these results, the proposed method shows satisfactory and encouraging results make it efficient to cope with some difficult such as variations of light conditions, complex background, and different kinds of license plates.

5. Concluding Remarks

We proposed an effective method for LPR system by using the mean shift algorithm and the Fuzzy ARTMAP neural network classifier, which increased the recognition rate of the system. The binarization method provided a good result which confirms to the final recognition rate.

However, the majority of character misclassification problems was due to similar characters, such as 1 and I, 0

and O, 2 and Z, 5 and S, and 8 and B. Especially, misclassification occurred in the cases of "8 -- B". The evident solution is the introduction of a priori knowledge for the kind of characters to be recognized (letter or number). However, with this assumption, the LPR process would be country specific.

We are currently undertaking research for extracting key points from the vehicle mask on the basis of license plate position and creating a digital signature for every vehicle model. Moreover, for under-vehicle inspection, it is assumed that a template under-vehicle image for each inspected vehicle has been archived into a database in advance. Based on the incoming vehicle license plate, the respective template image is retrieved from the database and then compared to the one acquired during real-time under-vehicle inspection.

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