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퍼지 ARTMAP에 의한 한글 차량 번호판 인식 시스템 설계

Design of a Korean Character Vehicle License Plate Recognition System

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요 약

Recognizing a license plate of a vehicle has widely been issued. In this thesis, firstly, mean shift algorithm is 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. We then present an approach to recognize a vehicle's license plate using the Fuzzy ARTMAP neural network, a relatively new architecture of the neural network family. We show that the proposed system is well to recognize the license plate and shows some compute simulations.

키워드 : 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. 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.

we first discuss a License Plate Segmentation. This part consists of preprocessing in order to detect the RoI in ambient illumination conditions. The preprocessing

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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 Euclidean metric allows a single bandwidth parameter for each domain

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

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 indiscriminately blurs the image, removing not only the noise but also salient information. Discontinuity preserving smoothing techniques, on the other hand, adaptively reduce the amount of smoothing near abrupt change in the structure. 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 bandwidth in the spatial domain and the range domain are denoted as h_s and h_r, respectively. Let x_i and z_i, $j=1,2,\cdots,n$, be the d-dimensional input and filtered image pixels in the joint spatial-range domain.

Table I. Discontinuity Preserving Smoothing

Input : image I
1. For each $j=1,2,\cdots,n$, run the mean shift filtering procedure for x_j and get filter image pixels z_j, as (1). Initialize *k=1* and $y_{i,k}=x_j$ (2). Compute $y_{i,k+1} = \frac{\sum_{i=1}^{n} x_i g\left(\left\| \frac{x-x_i}{h} \right\|^2 \right)}{\sum_{i=1}^{n} g\left(\left\| \frac{x-x_i}{h} \right\|^2 \right)}$, until convergence, and $y=y_{i,c}$. Where $g(x) = -k_N{}'(x) = \begin{cases} c & \|x\| < 1 \\ 0 & otherwise \end{cases}$. (3). Assign $z_i = (x_i^s, y_{i,c}^r)$. 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 $\{C_p\}_{p=1,2,\cdots,m}$ 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. For each $j=1,2,\cdots,n$, assign $L_j = \{p \mid z_j \in C_p\}$ 4. Eliminate spatial regions that are smaller than M pixels

Since this process takes into account simultaneously both the spatial and range information of the image, it can achieve a high quality, 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 correctly differentiate the license plate regions from others. 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 intensity, and position of the region. Some features, however, can only 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.

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.

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

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

$$ratio = \frac{c_{\max} - c_{\min} + 1}{r_{\max} - r_{\min} + 1} \quad (3)$$

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

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

Those candidate regions whose measurements fulfill the criteria orientation <35°, 2<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, there are still many candidate regions 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

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

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

The next part is the 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 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○ and height > 32 pixels) are deleted. The remaining objects are then forwarded to Fuzzy ARTMAP after a well defined preparation process, which includes character segmentation calculating the standard deviation of columns and rows, and, finally, transformation of each character to the size of the input vector of the Fuzzy ARTMAP. Fig 3 presents examples of license plate processing with the proposed algorithm.

After the Character Segmentation is finished, the next problem is character recognition. A combination of neural and fuzzy techniques (Fuzzy ARTMAP) 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.

Fuzzy ARTMAP consists of two fuzzy ART modules (ART_a and ART_b). The parameters of these networks are designated respectively by the subscripts a and b. The two Fuzzy ARTs are interconnected by a series of connections between the F_2 layers of ART_a and ART_b. These connections form what is called the *map field Fab*. The map field is used to form predictive associations between categories and to realize the match tracking rule, whereby the vigilance parameter of ARTa increases in response to a predictive mismatch at ARTb.

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

$$I = (a, a^c) = (a_1,\cdots,a_M, a_1^c,\cdots,a_M^c) \quad (6)$$

where

$$a_i^c = 1 - a_i \quad 1 \le i \le M_a$$

The F_1^a activity vector is denoted by $x^a = (x_1^a,\cdots,x_{2M_a}^a)$ and the F_2^a activity vector with N_a number of categories is denoted by $y^a = (y_1^a,\cdots,y_{2N_a}^a)$. M_a and N_a are arbitrary. For ARTb, $O_o = (b_1,\cdots,b_{M_b})$, $O = (b, b^c)$. The F_1^b activity vector is denoted by $x^b = (x_1^b,\cdots,x_{2M_b}^b)$ and the F_2^b activity vector with N_b number of categories is denoted by $y^b = (y_1^b,\cdots,y_{N_b}^b)$. M_b and N_b are also arbitrary. For the inter-ART modules, the map field F_{ab} output vector is denoted by $x^{ab} = (x_1^{ab},\cdots,x_{N_b}^{ab})$, and let $w^{ab} = (w_{j1}^{ab},\cdots,w_{jN_b}^{ab})$ 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 ARTa or ARTb categories is active. The F^{ab} output vector x^{ab} obeys

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

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 ARTa vigilance parameter ρ_a, equals the baseline vigilance, $\overline{\rho_a}$ at the beginning of every input presentation. When Fuzzy ARTMAP receives an input/output pair(I_o/O_O), ARTa chooses the Jth node of F_2^a and ARTb chooses the Kth node of F_2^b. When both ARTa and ARTb are active and $x^{ab} \neq 0$, then the input/output pairs are associated with the equation:

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

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, hence, forces the ARTa module to search for another category suitable to be associated with the desired output vector. ρa is then set back to the baseline vigilance parameter, $\bar{\rho}$, for every step of learning trial.

3. Simulation Results

The characters used to test the performance of the algorithm were extracted from a wide variety of images of vehicles. They are not idealized representations. The origin of these characters means that they are very varied in their size, orientation, completeness and method collection.

A lot of templates are 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 are shown in Fig 1.

(a)

(b)

(c)

(d)

(e)

Fig. 1. Step for license plate segmentation (a) Initial image. (b) Result of mean shift algorithm and edge detection. (c) Plate detection. (d) Binary image. (e) Successful segmentation of character

The inputs of Fuzzy ARTMAP algorithm are the images of numbers and letters on vehicle license plates. The testing set has 300 characters, around 96% of the characters have better quality, the others are all degenerate to different degree.

4. Conclusion and Future Extensions

This paper presented an effective character recognition method based on mean shift algorithm and a Fuzzy ARTMAP neural network classifier which increased the recognition rate of the system. The proposed binarization method provides a good result which conforms to the final recognition rate.

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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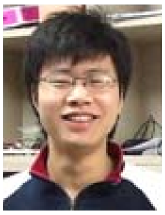
저 자 소 개



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