# SMART RECOGNITION SYSTEM FOR THE ALPHANUMERIC Content in Car License Plates 

A. Akoum, B. Daya<br>Lebanese University, Institute of Technology, P.O.B. 813, Saida, Lebanon

P. Chauvet<br>Institut de Mathématiques Appliquées, UCO, CREAM/IRFA, 3, place André-Leroy BP10808 - 49008 Angers - France

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#### Abstract

A license plate recognition system is an automatic system that is able to recognize a license plate number, extracted from an image device. Such system is useful in many fields and places: parking lots, private and public entrances, border control, theft and vandalism control. In our paper we designed such a system. First we separated each digit from the license plate using image processing tools. Then we built a classifier, using a training set based on digits extracted from approximately 350 license plates. Our approach is considered to identify vehicle through recognizing of its license plate using two different types of neural networks: Hopfield and the multi layer perceptron "MLP". A comparative result has shown the ability to recognize the license plate successfully.


## 1 INTRODUCTION

Optical character recognition has always been investigated during the recent years, within the context of pattern recognition (Swartz, 1999). The broad interest lies mostly in the diversity and multitude of the problems that may be solved (for different language sets), and also to the ability to integrate advanced machine intelligence techniques for that purpose; thus, a number of applications has appeared (Park, 2000; Omachi, 2000).

The steps involved in recognition of the license plate are acquisition, candidate region extraction, segmentation, and recognition. There is batch of literature in this area. Some of the related work is as follows: (Hontani, 2001) has proposed method heart extracting characters without prior knowledge of their position and size. (Cowell, 2002) has discussed the recognition of individual Arabic and Latin characters. Their approach identifies the characters based on the number of black pixel rows and columns of the character and comparison of those values to a set of templates or signatures in the database. (Yu, 2000) have used template matching. In the proposed system high resolution digital
camera is used for heart acquisition.
The intelligent visual systems are requested more and more in applications to industrial and deprived calling: biometrics, ordering of robots, substitution of a handicap, plays virtual, they make use of the last scientific projections in vision by computer (Daya, 2006), artificial training and pattern recognition (Prevost, 2005).

The present work examines the recognition and identification -in digital images- of the alphanumeric content in car license plates. The images are obtained from a base of abundant data, where variations of the light intensity are common and small translations and or rotations are permitted. Our approach is considered to identify vehicle through recognizing of it license plate using, two processes: one to extract the block of license plate from the initial image containing the vehicle, and the second to extract characters from the licence plate image. The last step is to recognize licence plate characters and identify the vehicle. For this, we used two different neural networks with $42 \times 24$ neurons as the dimension of each character. The network must memorize all the Training Data (36 characters). For the validation of the network, we have built a program that can read the sequence of characters,
split each character, re-size it and finally display the result on a Notepad editor.

The rest of the paper is organized as follows: In Section 2, we present the real dataset used in our experiment. We give in section 3 the description of our algorithm which extracts the characters from the license plate. Section 4 gives the experimental results the recognizing of characters using two types of neural networks architecture. Section 5 contains our conclusion.

## 2 DATABASES

The database (Base Images with License) contains images of good quality (high-resolution: 1280x960 pixels resizes to $120 \times 180$ pixels) of vehicles seen of face, more or less near, parked either in the street or in a car park, with a negligible slope.

The images employed have characteristics which limit the use of certain methods. In addition, the images are in level of gray, which eliminates the methods using color spaces.


Figure 1 : Some examples from the database training.

## 3 LICENSE PLATE CHARACTERS EXTRACTING

Our algorithm is based on the fact where an area of text is characterized by its strong variation between the levels of gray and this is due to the passage from the text to the background and vice versa (see fig. 1.). Thus by locating all the segments marked by this strong variation and while keeping those that are cut by the axis of symmetry of the vehicle found in the preceding stage, and by gathering them, one obtains blocks to which we consider certain constraints (surface, width, height, the width ratio/height,...) in order to recover the areas of text candidates i.e. the areas which can be the number plate of the vehicle in the image.


Figure 2: Selecting of license plate.

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Figure 3: Extracting of license plate.

We digitize each block then we calculate the relationship between the number of white pixels and that of the black pixels (minimum/maximum). This report/ratio corresponds to the proportion of the text on background which must be higher than 0.15 (the text occupies more than $15 \%$ of the block).

First, the block of the plate detected in gray will be converted into binary code, and we construct a matrix with the same size block detected. Then we make a histogram that shows the variations of black and white characters.

To filter the noise, we proceed as follows: we calculate the sum of the matrix column by column, then we calculate the min_sumbc and max_sumbc representing the minimum and the maximum of the black and white variations detected in the plaque. All variations which are less than 0.08 * max_sumbc will be considered as noises. These will be canceled facilitating the cutting of characters.


Figure 4: Histogram to see the variation black and white of the characters. The characters are separated by several vertical lines by detecting the columns completely black.

To define each character, we detect areas with minimum variation (equal to min_sumbc). The first detection of a greater variation of the minimum value will indicate the beginning of one character. And when we find again another minimum of
variation, this indicates the end of the character. So, we construct a matrix for each character detected.

The Headers of the detected characters are considered as noise and must be cut. Thus, we make a 90 degree rotation for each character and then perform the same work as before to remove these white areas.


Figure 5: Extraction of one character.
A second filter can be done at this stage to eliminate the small blocks through a process similar to that of extraction by variations black white column.

Finally, we make the rotation 3 times for each image to return to its normal state. Then, we convert the text in black and change the dimensions of each extracted character to adapt it to our system of recognition (Hopfield and MLP neural network).

## 4 RECOGNIZING OF CHARACTERS USING OUR APPROACH NEURAL

The character sequence of license plate uniquely identifies the vehicle. It is proposed to use artificial neural networks for recognizing of license plate characters, taking into account their properties to be as an associative memory. Using neural network has advantage from existing correlation and statistics template techniques (B. Kroese, 1996) that allow being stable to noises and some position modifications of characters on license plate.

Our approach is considered to identify vehicle through recognizing its license plate using, Hopfield networks with $42 \times 24$ neurons as the dimension of each character. The network must memorize all the Training Data ( 36 characters). For the validation of the network we have built a program that reads the sequence of characters, to cut each character and resize it and put the result on a Notepad editor. A comparison with an MLP network is very appreciated to evaluate the performance of each network.

For this analysis a special code has been developed in MATLAB. Our Software is available to do the following:

1) Load a validation pattern.
2) Choose architecture for solving the character recognition problem, among these 6 architectures:

- "HOP112": Hopfield architecture, for pictures of $14 \times 8$ pixels (forming vector of length 112).
- "HOP252": Hopfield, for $21 \times 12$ pixels.
- "HOP1008": Hopfield, for 42x24 pixels.
- "MLP112": Multi Layer Perceptron architecture, for pictures of $14 \times 8$ pixels.
- "MLP252": MLP, for $21 \times 12$ pixels.
- "MLP1008": MLP, for $42 \times 24$ pixels.

3) Calculate time of processing of validation (important for "real applications").


Figure 6: The graphic interface which recognizes the plate number and posts the result in text form.

For our study, we used 3 kinds of Hopfield Networks and 3 kinds of MLP Networks, always with one hidden layer. In the case of MLPs, we train one MLP per character; it means that there are 36 MLPs for doing the recognition. In the case of Hopfield there is only one network that memorizes all the characters.

Table 1: The performance of each Neural Network Architecture (multi layer perceptron and Hopfield).

| Neural <br> Network | Number <br> of <br> neurons | Total <br> Symbols | Total <br> Errors | Perf <br> $(\%)$ |
| :---: | :---: | :---: | :---: | :---: |
| HOP | 1008 | 1130 | 144 | $87 \%$ |
| MLP | 1008 | 1130 | 400 | $64 \%$ |
| HOP | 252 | 1130 | 207 | $84 \%$ |
| MLP | 252 | 1130 | 255 | $80 \%$ |
| HOP | 112 | 1130 | 342 | $69 \%$ |
| 'MLP | 112 | 1130 | 355 | $68 \%$ |

The table 1 shows the performance of each neural architecture for the six different cases. Tables 2 and 3 "see appendix" shows all the recognitions for all the patterns. First column corresponds to the file's name of the plate number; second column the plate number observed with (our eye) and from
columns 3 to 5 there is the plate number that each architecture has recognized. The last row corresponds to the average processing time that takes for each network.

In the case of Hopfield recognition, when the network doesn't reach a known stable state it gives the symbols "?". Hopfield Networks have demonstrated better performance $87 \%$ than MLPs regarding OCR field. A negative point in the case of Hopfield is the processing time, in the case of pictures of $42 \times 24$ pixels ( 90 seconds average, versus only 3 seconds in the case of pictures of $21 \times 12$ pixels). It can be observed also that cases "HOP1008" and "HOP252" don’t present an appreciable difference regarding performance.

## 5 CONCLUSIONS

The purpose of this paper is to investigate the possibility of automatic recognition of vehicle license plate.

Our algorithm of license plate recognition, allows to extract the characters from the block of the the plate, and then to identify them using artificial neural network. The experimental results have shown the ability of Hopfield Network to recognize correctly characters on license plate with probability of $87 \%$ more than MLP architecture which has a weaker performance of $80 \%$.

The proposed approach of license plate recognition can be implemented by the police to detect speed violators, parking areas, highways, bridges or tunnels.

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## APPENDIX

Table 2: The recognition for some patterns with different numbers of neurons (Hopfield Network).

| Seq | Real plate number (eye) | HOP1008 | HOP252 | HOP112 |
| :---: | :---: | :---: | :---: | :---: |
| 'p1' | '9640RD9' | '9640R094' | $\begin{aligned} & \hline \text { '9640R09 } \\ & 4^{\prime} \end{aligned}$ | '9640R?94 |
| 'p2' | $\begin{aligned} & \text { '534DDW7 } \\ & \text { 7' } \end{aligned}$ | '534DD?77' | $\begin{aligned} & \text { '534DD?7 } \\ & \text { 7' } \end{aligned}$ | $\begin{aligned} & \text { '534DD?7 } \\ & \text { 7' } \end{aligned}$ |
| 'p3' | '326TZ94' | '326TZ94' | '326TZ94' | '325TZ9?' |
| 'p4' | '6635YE93 | '66J5YES?' | 'B??5YE? ?' | 'B???YE?? |
| 'p5' | '3503RC94 | '3503RC94' | $\begin{aligned} & \text { '35O3RC9 } \\ & 4^{\prime} \end{aligned}$ | $\begin{aligned} & \hline \text { '3503RC9 } \\ & 4^{\prime} \end{aligned}$ |
| 'p6' | '7874VT94 | '7874VT94' | $\begin{aligned} & \text { '7874VT9 } \\ & 4^{\prime} \end{aligned}$ | $\begin{aligned} & \text { '7874VT9 } \\ & 4^{\prime} \\ & \hline \end{aligned}$ |
| $\begin{aligned} & \text { Tim } \\ & \mathrm{e} \\ & \hline \end{aligned}$ | -- | 90 sec | 3 sec | 2 sec |

Table 3: The recognition for all some patterns with different numbers of neurons (MLP network).

| Seq | Real plate number (eye) | MLP1008 | MLP252 | MLP112 |
| :---: | :---: | :---: | :---: | :---: |
| 'p1' | $\begin{aligned} & \text { '9640RD9 } \\ & 4^{\prime} \end{aligned}$ | '964CR094' | '56409D94' | $\begin{aligned} & \hline \text { '2B40PD3 } \\ & 4^{\prime} \\ & \hline \end{aligned}$ |
| 'p2' | $\begin{aligned} & \hline 534 \mathrm{DDW} \\ & 77{ }^{\prime} \\ & \hline \end{aligned}$ | '53CZD677' | '53CDD877 | $\begin{aligned} & \hline \text { '53WDD9 } \\ & 77 \text { ' } \\ & \hline \end{aligned}$ |
| 'p3' | '326TZ94' | '32SSZ8C' | '326T794' | '328TZ3C' |
| 'p4' | $\begin{aligned} & \hline \text { '6635YE9 } \\ & 3^{\prime} \\ & \hline \end{aligned}$ | '8695YE8O' | 'BE3SYE98 | $\begin{aligned} & \hline \text { 'E535YEB } \\ & 3^{\prime} \\ & \hline \end{aligned}$ |
| 'p5' | $\begin{aligned} & \hline \text { '3503RC9 } \\ & 4^{\prime} \\ & \hline \end{aligned}$ | '35CO3C94' | '5503RC94' | $\begin{aligned} & \text { '3503PC2 } \\ & 4^{\prime} \\ & \hline \end{aligned}$ |
| 'p6' | $\begin{aligned} & \text { '7874VT9 } \\ & 4^{\prime} \end{aligned}$ | 'F674VT94' | '7574V394' | $\begin{aligned} & \text { '7S74VT3 } \\ & 4^{\prime} \end{aligned}$ |
| Time | -- | 25 sec | 3 sec | 2 sec |

