DETECTION AND AUTOMATIC IDENTIFICATION OF CAR PLATES

C.A. Castro Daniel [1]
C.A. Osvaldo Fillia[1]
C.A.. Diez Mauro[1]
Lic. Lanzarini Laura[2]
Eng. De Giusti Armando.[3]
Laboratory of Investigation and Development in Computer Sciences.[4]
Department of Computer Sciences - Faculty of Exact Sciences.
National University of La Plata,
Argentina.

Summary:

This work is a pattern recognition application using digital images processing and neural networks, applied to the automatic recognition of car plates.

There is a wide range of problems to be solved, which go from the segmentation of the useful section of the image, to the use of neural networks to carry out a correct identification.

The purpose of this work is not only to achieve the implementation of a specific tool to classify car plates, but also to compare the solutions provided by applying digital images processing and neural networks.

Key Words: Digital Images Processing - Pattern recognition - Neural Networks

[1] Computer Analyst. Department of Computer Sciences, Faculty of Exact Sciences, UNLP.

[2] Full-time Co-Chair Professor, Department of Computer Sciences, Faculty of Exact Sciences, UNLP.

[3] Director of the LIDI. Principal Researcher of the CONICET. Full-time Chair Professor, Department of Computer Sciences, Faculty of Exact Sciences, UNLP.

[4] LIDI. Laboratorio de Investigación y Desarrollo en Informática, Dpto. de Informática, Fac. de Cs. Exactas, UNLP. Calle 50 y 115 - 1er piso - 1900 La Plata - Buenos Aires - Argentina.
Tel / Fax: 54 - 21 - 22 7707
E-Mail: lidi @ lidi.info.unlp.edu.ar

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Introduction

Pattern recognition is the ability of identifying and classifying images. In general, systems developed in this area are set to carry out this task by reproducing human behavior. For example, if the images to be classified are documents, and the patterns of interest are of an alphanumeric nature, the aim of the system would be to recognize and classify these documents as proficiently as a human being would do it.

In this sense the system should, in the first stage, be able to differentiate useful information from non-relevant details.

Unfortunately, there are several aspects which are inherent to images and which make their analysis rather difficult. Changes as simple as the font type in a text, or the point of view from which a 3D image is viewed, may cause different renderings of the same object. Thus, the system should also be capable of generalizing the data underlying knowledge in order to use them in similar circumstances [GO92].

This paper introduces a pattern recognition application for the automatic detection of car plates to improve the currently existing systems used to issue tickets for violations to traffic laws.

This type of system helps traffic police to detect infringers and to provide hard-to-refute evidence.

In particular, speed limits violation in highways and roads are controlled by means of systems provided with a video camera which captures the image of the infringer as well as that of the speed sensors.

The current procedure is as follows: the image of the vehicle is automatically entered and the car plate is introduced by the operator. After this, a document is drawn up with relevant vehicle information, owner, cause and amount of the traffic ticket, and geographic data of the place where the infringement took place.

Thus, there is the need for a tool which allows to carry out a completely automatic recognition.

The characteristics of this problem led to a development covering different areas. It is thus an important contribution from the point of view of the comparison of different theoretical decision methods, which use a *decision function* or a *discriminating function* in order to classify a given pattern.

The best results were obtained by means of the application of self-organizing maps (SOM). This type of architecture is characterized not only for automatically grouping patterns in their corresponding classes, but also for noise tolerance. In addition to this, since this is a network which separates the training stage from the classification one, once trained, it has a minimum response time [KO97].

Objective

The main purpose of this work is the development of an environment which is able to automatically recognize car plates from digital images.

This requires different techniques to be known and used, in order to compare the time needed for calculation with the reliability of the results obtained.

As a first approach, a statistical recognition of patterns was used, but it unfortunately yielded unsatisfactory results.

The later introduction of recognition methods based on neural networks resulted in a sizeable improvement of final results.

Implementation Aspects

Images were taken with a Panasonic camera located at a fixed point in the street, and were digitized with an SE100 Video Blaster board.
The images used were of 300 x 200 pixels and 256 gray levels in BMP format, similar to the one shown in Fig. 1.

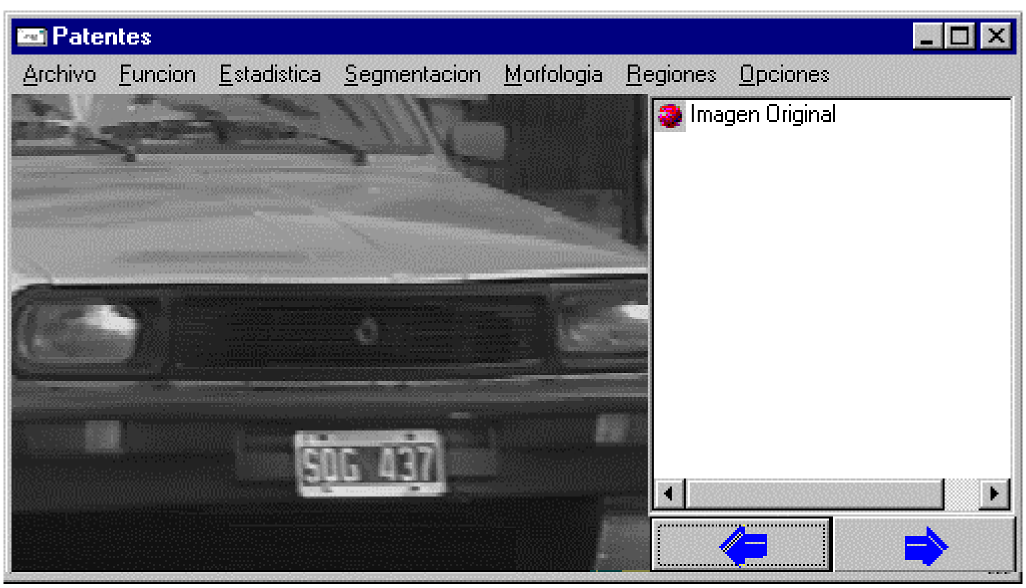


Fig. 1

For the recognition of car plates several stages should be carried out.

1) Location of the car plate in the image:

Since the images portray moving vehicles, it is not possible to know beforehand the exact location of the car plate in the image. Even though it is true that given a fix camera position taking images of cars at similar distances, the region of interest should be located at the lower part of the image, this is not always the case due to the speed of cars; therefore it was decided to analyze the whole image.

It is not possible, either, to readily separate the car plate from the background, since gray levels vary according to lightning, the color of the car, and so on.

Taking all these facts into account, it was decided to analyze the image as a whole and use the concentration at the borders of the car plate as an indicator of its position.

The following stages were therefore necessary:

1.1) **Binarization**: For this stage it is not necessary to have a good definition image, since the car plate region is detected by using the concept of borders concentration. Therefore, the image was first binarized in order to apply a borders detector. With this in mind, the histogram mean value was used as the thresholding limit. [BA94] [GO92]

As a way of reducing the algorithm running time, and as the image is converted to zeros and ones, a list is built with the blank pixels. These will be used for the following stages (Fig. 2).

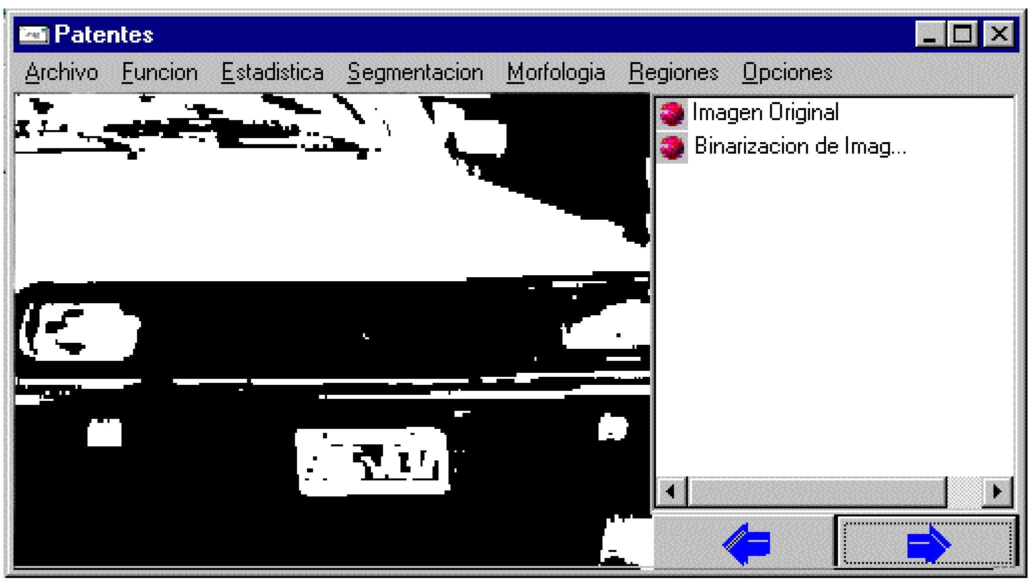


Fig. 2

1.2) **Detection and elimination of large regions**: Before working on the borders, a regions detector was applied in order to take large regions to the background color, thus reducing the amount of borders. (Fig. 3).

Fig. 3

1.3) **Borders Detection**: then a mask considering the value of the gradients in the four directions (horizontally and vertically) was applied to the list of blank pixels [JA89]. (Fig. 4)

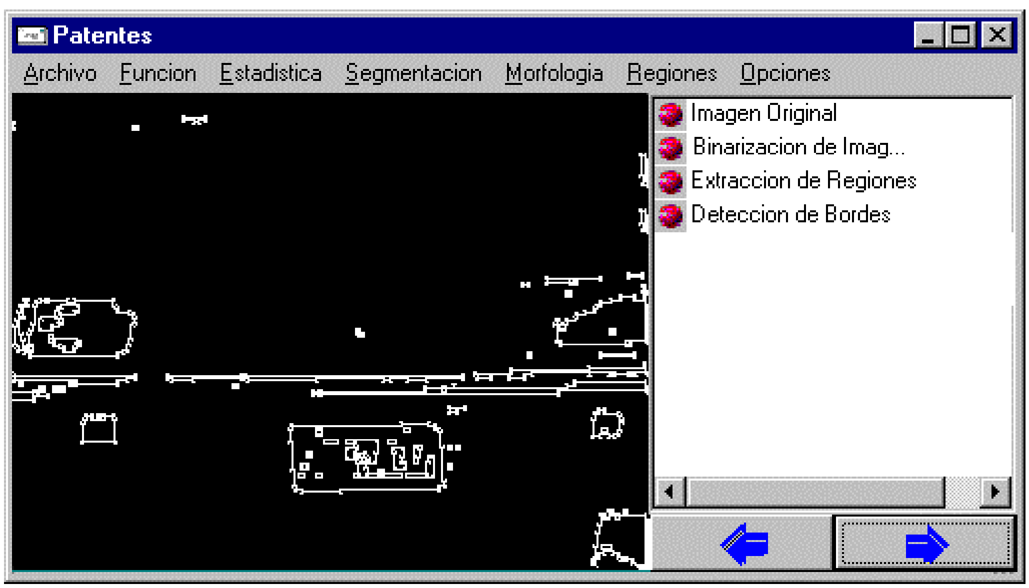


Fig. 4

1.4) **Borders concentration measurement**: the image was swept using a window of 100 x 30 pixels. The location of the window with more blank pixels will reveal the location of the car plate.
At this point, the size of the sweeping window is very important. If it is too small it could take a maximum value in any position, be it inside the car plate itself or at any other place on the car (e.g., the engine grill). On the other hand, if it is too big, more borders than needed would be included, and it would thus be more difficult to locate the desired area. (Fig. 5).

The size of the window was determined according to the dimensions of the car plates of the 74 acquired images. However, this size should be adjusted by means of a calibration process if acquisition parameters are modified. It is currently possible to set the size of the window for each application of the algorithm.

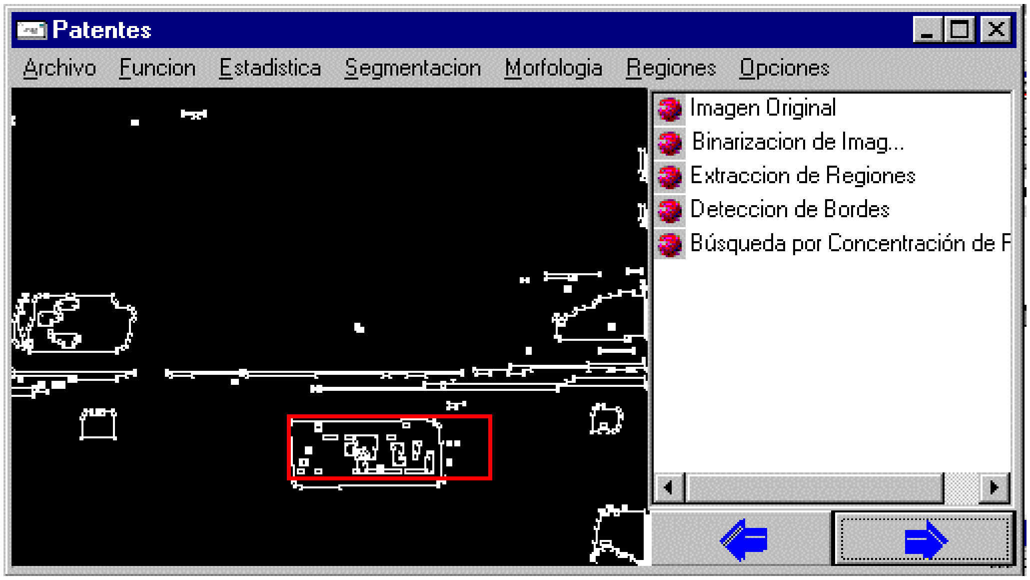


Fig. 5

1.5) **Segmentation**: Once the region is recognized, it is cut out from the larger image (Fig. 6).

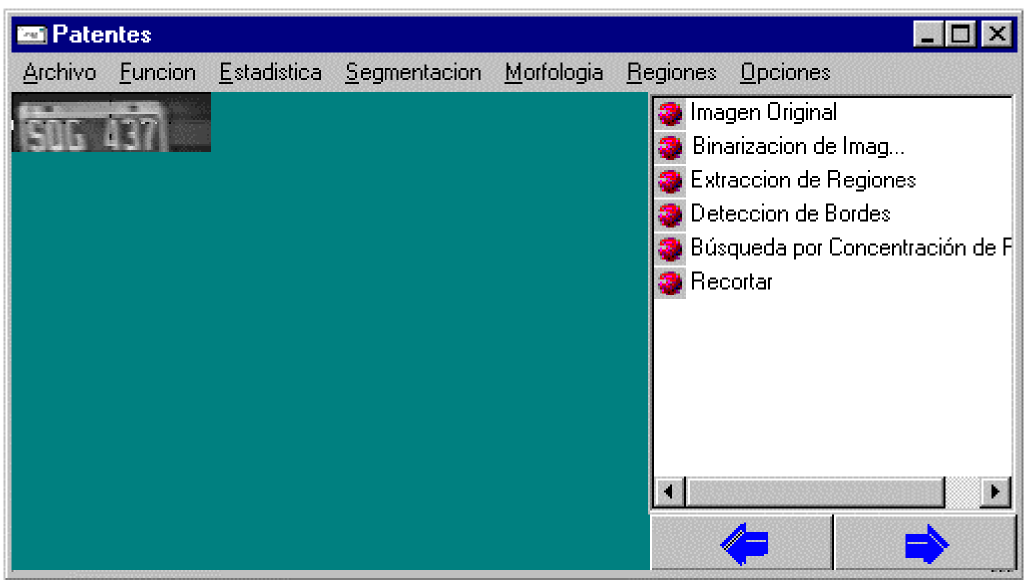


Fig. 6

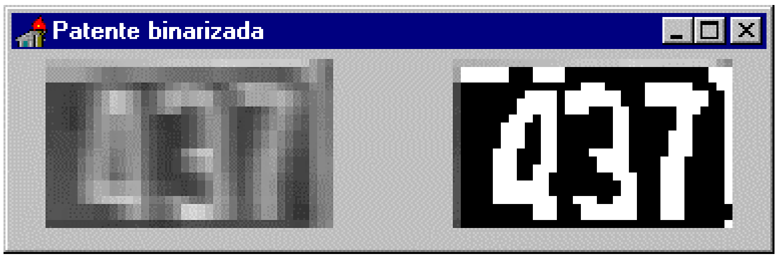
2) **Car plate analysis**:

Once the car plate is cut out **from the original image**, the following procedure is followed:

2.1) **Histogram equalization:** in order to better differentiate the car plate gray levels. Remember that the equalization distributes the histogram between 0 and 255, so if it is applied to a clear image, gray level changes will be better distinguished, but if it is applied to a good-contrast image, it will not have any effect on the image.

2.2) **Exponential enhancement**: to further separate the intermediate gray levels between the pixels that clearly belong to the car plate and those which belong to the background an exponential function was applied. This operation increases the distance between the lighter values (which belong to the letters and numbers on the car plate) and the background, which is readily taken to 0.

2.3) **Thresholding**: after a statistical analysis of the image resulting from the previous step, a threshold or limit value was calculated in order to obtain an output with only two levels, 0 and 1. Note the improvement as compared with the previous threshold.



3) **Segmentation**:
The connected zones are labeled considering connectivity 4 and grouping the areas smaller than 0.05% of the size of the image. This last condition allows to considerably reduce classification error. However, sometimes the elements of the car plate are touching each other because of the noise of the input image. This can be detected by calculating the area of the labeled region. In these cases, the region was segmented at its middle point. Even though there are different feasible application techniques for this kind of cases, no significant improvements have been obtained as compared with the time needed for their application.

Thus, the elements which are part of the car plate are separately obtained. Now the identification of the segmented area must be carried out.

4) **Classification:**
In order to obtain an immediate classification of the segmented region, theoretical decision methods were used. That is, a *decision function* or a *discriminating function* were used to classify a given pattern.

Thus, if $\mathbf{x} = (x_1, x_2, ..., x_n)^t$ represents an n-dimensional pattern, and given M classes, $w_1, w_2, ..., w_M$, the basic problem of the recognition of patterns by means of a theoretical decision consists in finding M decision functions $d_1(x), d_2(x), ..., d_M(x)$ with the following property:
If pattern $\mathbf{x}$ belongs to class w_i, then $d_i(\mathbf{x}) > d_j(\mathbf{x})$ for $j= 1..M; j\neq i$

Within theoretical decision methods, there are different possible solutions from the point of view of digital images processing.

During a first stage, a **minimum distance sorter** was used, where each class was represented by its mean vector. Thus, given a pattern to classify, the distance to the

representative vectors of each class could be calculated. At the end of this procedure, the pattern was considered to be a member of the nearest class.
This method, despite its simplicity, yields very good results when the distance between the means of the different classes is large as compared with the dispersions of the elements belonging to the class around their mean.
In the case of the recognition of the elements in a car plate, a counterpropagation neural network was used as a way of measuring this sorter. The results obtained are presented in the following section.

As for **correlation correspondence**, it was discarded because in this case what is analyzed is the correspondence between a sub-image and a portion of the original image. In addition to this, the method carries a high computational cost as well as a large error factor, specially for border pixels.

Other plausible classification method could be the use of the Bayes sorter. However, in order to use this sorter it would be necessary to know the probability density function of the car plate elements [TA98]; and there were not enough samples to do that.

On the other hand, neural networks present several advantages when working with patterns recognition:
Input patterns characterization:
Even though it is possible to use a vector with characteristics of the image to be classified as a pattern, this stage can be skipped with neural networks and directly process the image under study, thus avoiding both processing time and the unavoidable underlying subjectivity when choosing and measuring such characteristics [MA94].

Automatic recognition of the existing classes:
Even though the topic of this paper seems to be circumscribed to a problem limited to characters recognition, the noise present in the original image causes the appearance of rather different patterns within the same class. The use of a competitive network will result in a knowledge of the nature of input data, which will in turn facilitate the classification process.

Noise tolerance:
It is important to work with a network which is capable of storing representative information of each class through a training process, instead of storing information of the isolated patterns. This will allow to count with a greater interpolating capacity, which reduces noise [FRE93] [KO97].

For all these reasons, the use of neural networks as a way of having a fast and noise-tolerant sorter was considered.

Results Obtained:
In this case, not a set of characteristics of the letters or numbers cut out from the image, but the segmented pixels from the binarized region, were considered as patterns. Since it was necessary to have fixed-dimension patterns, the environment was completed with the background color in the following way: not more than three rows at the top and

bottom, and not more than two at the sides. When necessary, the image was enlarged to have the expected amount of pixels. This procedure mostly solved all scale-related problems, which were due to the distance between the vehicle and the camera.

Even though when using neural networks letters and numbers can be simultaneously classified, the idea of dividing the problem in two phases to classify letters and numbers separately was initially considered [RA95]. The position of the element in the car plate determines which of the two networks will be used. Since the process carried out is the same in both cases, only the networks analyzed for the recognition of numbers will be described (in the case of letters recognition, only the amount of neurons of the hidden and the output layers should be properly modified).
The use of a supervised learning architecture was initially considered in order to count with a fast learning process which would allow to arrive to the expected answer with an acceptable error rate [YO89].

A BackPropagation network with 170 neurons in the input layer, 4 in the output layer (binarily representing a number between 0 y 9) and 50 neurons in the hidden layer was used.
During the training stage, the learning process of the neurons from the hidden layer was measured using weights variation. This allowed to reduce the amount of neurons to 25 [FRE93]. However, and despite the fact that the error at this stage was 0.001, no good results were obtained for patterns which had not been included during the training stage. This was due to the noise present in the input data and to the low interpolating capacity of this type of architecture.

A counterpropagation network was then considered, with 170 neurons in the input layer, 4 in the output layer, and 30 in the hidden layer.

As a way of simulating the behavior of the minimum distance sorter, the competitive layer was trained by modifying only the weights of the winning neuron. This resulted in each neuron of the hidden layer having an associate input weights vector corresponding to the mean vector of each class.

Due to the dimensions of the input patterns, it was necessary to use representative input weights of the classes to be classified. The patterns used were those associated to the noiseless numbers [AR96].

However, the best results were obtained when slightly modifying the behavior of the previous network by allowing the competitive neuron not only to learn but to do so in an environment. This resulted in a self-organizational map (SOM) [KO97] [FRE93].

In order to avoid the effect of input noise, patterns were blurred in a pixel, which improved the classification process in a 10% [KO97] [GHO98].

Conclusions

A process for the automatic recognition of car plates using statistical recognition techniques and neural networks has been presented.

A Delphi processes library has been implemented for the development of this work and is available for application not only to this problem but to any other problem in the pattern recognition area.

All documentation is available at the L.I.D.I. (Laboratorio de Investigación y Desarrollo en Informática), 50 y 115 1er. Piso, La Plata.

References

[AR96]	Fuzzy Parameter Adaptation in Optimization: Some Neural Net Training Examples. Arabshahi, Choi, Marks ,Caudell. IEEE Computational Science & Engineering Spring 1996, Vol3- N° 1, pp. 57-65
[BA94]	Digital Image Processing Principles and Applications. Gregory A. Baxes. Editorial Jhon Wiley & Sons 1994.
[FRE93]	Redes neuronales. Algoritmos, aplicaciones y técnicas de programación. Freeman y Skapura. Editorial Addison-Wesley,1993.
[GHO98]	Incremental Communication for Multilayer Neural Networks: Error Analysis. A. A. Ghorbani and V. C. Bhavsar. IEEE Transactions on Neural Networks, January 1998, Volume 09, Number 01, pp. 68-83
[GO92]	Digital Image Processing. Rafael González and Richard Woods. Editorial Addison-Wesley Publishing Company, 1992.
[JA89]	Fundamentals of Digital Image Processing. Jain. Editorial Prentice-Hall, 1989.
[KO97]	Self-Organizing Maps (second edition). Kohonen. Springer, 1997.
[MA94]	Signal and Image Processing win Neural Networks. Timothy Masters. Editorial John Wiley & Sons, 1994
[RA95]	C++ Neural Networks and Fuzzy Logic (second edition). Rao and Rao. Editorial MIS:Press, 1995
[TA98]	Decision Rule for Pattern Classification by Integrating Interval Feature Values. Takahiko Horiuchi. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 20, No. 4, April 1998
[YO89]	Adaptive Pattern Recognition and Neural Networks. Yoh-Han Pao. Editorial Addison-Wesley 1989
[YU98]	Neural-Network Design for Small Training Sets of High Dimension J.-L. Yuan and T. L. Fine. IEEE Transactions on Neural Networks, March 1998, Volume 09, Number 02, pp. 266-281