CAR PLATE RECOGNITION BY NEURAL NETWORKS AND IMAGE PROCESSING

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ABSTRACT

In this paper we describe an experimental system for the recognition of Italian-style car license plates. Images are usually taken from a camera at a toll gate and preprocessed by a fast and robust 1-D DFT scheme to find the plate and character positions. Characters are classified by a multilayer neural network trained by the recently developed BRLS learning algorithm. The same neural network replaces both the traditional feature extractor and the classifier. The percentage of correctly recognized characters reaches the best scores obtained in literature, being highly insensitive to the environment variability, while the architecture appears best suited for parallel implementation on programmable DSP processors.

1. INTRODUCTION

Car license recognition is important in several fields of application:

- traffic control in restricted areas;
- automatic payment of tolls on highways or bridges;
- general security systems wherever there is the need of identifying vehicles.

Some approaches exist and have been described in literature. They are mainly based on pattern matching and normalized correlation with a large database of stored templates.

In this paper we describe an experimental system for the recognition of Italian-style car license plates. The system is based on the use of a feedforward neural network (FNN) trained with the Block Recursive LS algorithm (BRLS), described in [1] . This learning approach has been shown to guarantee high rates of convergence and properties of stability and robustness of the solution. The data at hand consist of digitized images of cars, acquired by a high-resolution 35 mm photo camera and collected in a Photo CD. The processed images (see Fig.1) are 390 by 480 pixel wide. The distance and the angle of view simulate a car passing through a toll gate.

The recognition process starts with the search and the extraction of the portion of the original image containing the car plate. The characters contained in the plate are localized by a robust processing using a non-traditional Discrete Fourier Transform (DFT), and subsequently isolated and classified by the neural network. The scores are validated by a post-processor which takes into account the syntax of Italian-style plates.

The neural network is trained off-line with a set of error-free synthetic characters, while competing approaches need a large database of real-world images. The fast training convergence and the surface error model adopted in the BRLS approach allow to find reliably a local minimum in the mean squared error (MSE) cost function with a high grade of generalization capability.

With respect to a recently published work [2] our approach is able to reduce the complexity of the learning phase (no feature extraction and pattern matching are required). The character recognition has been speeded up by the parallel architecture of the FNN. The algorithm has been tested on a workstation featuring a Pentium Pro PC 200 MHz processor and the Matlab software. The next step will be to write hand-optimized routines in a high-level language such as C++ or also assembler to enhance the processing speed.

2. OUTLINE OF THE ALGORITHM

The whole algorithm consists of the following sequential steps, each using a different and application-oriented approach.

Step1: Image preprocessing. The digitized image (Fig. 1) is preprocessed by tone equalization and contrast reduction. This technique has been preferred to other

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alternatives, such as edge enhancement, for the better robustness and suitability for the next processing stage.

Step2: Plate location detection and extraction. Empirical evidence suggests that dimensions of the car and the plate in the image acquired by a typical toll gate camera should not vary more than about 15%. This fact enables for a fast localization technique which avoids an expensive numerical search over large areas. The character spacing produces neat spatial harmonics in the horizonal direction, that can be detected by spectrum analysis.

In the presented system the horizontal stripe of the image containing the plate is found by maximizing the global energy of expected harmonics. The harmonic decomposition is accomplished by a row-wise DFT, followed by a synchronized average [5] in the spatial frequency domain, as shown in Fig. 2. This kind of processing uses the global energy estimated from harmonically related frequency bins as the detection statistic. For example, a single average will involve the periodogram estimates { P(k), k=1, 2, ...N/2 } [4] obtained from the DFT { X(k), k=1, 2, ...N } at bins 2, 4, 6, etc... In practice, a relatively robust estimator Q(p) of the harmonic standard deviation is employed [6] :

$$Q(p) = \frac{1}{K} \sum_{k=1}^{K<N/2} \text{abs}(X(kp)), \tag{1}$$

where the function abs(z) indicates the modulus of the complex argument. This particular estimator has been chosen also for the simplicity of implementation in most DSP processors and VLSI dedicated chips.

The vertical location of the plate is found roughly in the same way, by using a small column-wise DFT on the candidate(s) stripe(s) found in the previous step (Figs. 3, and 4).

Step 3: Character localization and segmentation. After the plate has been located, the relative image portion is quantized to binary values according to an adaptive threshold established directly through a two-class clustering of tones. The characters are segmented by finding white areas between columns with higher density of black pixels (Figs. 5 and 6).

Isolated black pixels are wiped out and the character is resized to the standard measure of (10 by 6) pixels after a factor-of-two decimation (Fig. 7).

Step 4: Recognition by the FNN. The FNN has been trained with the English character set by the BRLS algorithm [1] . For each character, several replicas shifted by one pixel in each direction have been presented to the FNN, in order to enhance the generalization capability [3] . The fast convergence of the algorithm, combined with the low misadjustment noise with respect to the classical backpropagation, has driven the working point of the network toward a well-behaved minimum. In fact, the BRLS algorithm is able to find an extremum surrounded by a nearly quadratic hypersurface, which is typical of a near Maximum Likelihood [4] (e.g. good) estimator of neuron weights.

The FNN used in this system was two-layered with 60 input, 30 hidden and 35 output neurons, that act as a demultiplexer of the 35 possible characters that can be found in Italian plates.

Step 5: Plate validation. The plate number is reconstructed from the recognized characters. Gross errors are limited by a comparison with a database of rules, describing the acceptable sequences of characters, according to the Italian legal plate numbering scheme.

The overall recognition rate of the system has been the 90% on a validation set of fifty real-world images, with 8% of rejection rate and one (2%) false recognition. The percentage of correctly recognized characters has reached the 98.7%. Most rejections happened with old and dusty plates, almost unreadable also by human eyes. This performance compares directly with the data reported in [2] .

3. DISCUSSION

The presented application is an example of the capability of neural networks to perform complex signal processing and classification tasks with real-world data.

The car-plate recognition is a relatively complex task, for the variety of environment and targets, and the ordinary presence of disturbing elements (dust, non-standard positioning of plates, rain, fog, etc...). In traditional systems, there exist separate procedures for image preprocessing, plate alignment, filtering, template correlation and winner selection. These algorithms are ideally sequenced, and rely on the robustness of previous stages to furnish a valid answer.

Algorithm sequencing may generate an unrecoverable loss of information at each step, further reducing the chance of arriving to a correct final decision.

In the proposed experimental system, a single FNN replaces several algorithm blocks required by traditional processing with a parallel architecture realizable with DSP VLSI circuits, having the capability of a very high speed of recognition at low costs.

It is worth to point out that a state-of-the art classification capability performance has been achieved with a training set formed exclusively by artificially-generated examples.

The BRLS algorithm once more demonstrated its intrinsic resistance to the presence of ill-shaped regions of the error surface (non-convex, nearly flat) and of local minima that do not meet the basic requirements for being locally good estimators of neuron parameters. The fast (superlinear) convergence speed of the BRLS was not a prerequisite for the particular application, since the training can be done off-line. Anyway, the BRLS learning reduced greatly the setup times for experiments and is suitable for on-line adaptive training, when needed to compensate for miss-modelling.

The search for typical spatial harmonics generated by the nearly regular character spacing on the plate is also a distinctive feature of the proposed procedure, remarkable for the overall robustness and near optimality of the detection. The Discrete Cosine Transform (DCT) could be considered as a substitute for the DFT, with possible reduction in computational costs, due to the real arithmetic involved.

This simple recognition system demonstrates that most existing approaches are excessively complicated both from the theoretical and algorithmical points of view. In fact a judicious choice made on statistics and distinct modelling features of the data at hand can be coupled with well known general-purpose tools (transforms, rough statistical estimators, neural networks, optimization algorithms) to generate an information-preserving processing with state-of-the-art performance.

4. CONCLUSIONS

The presented application is an example of the capability of neural networks to perform complex signal processing and classification tasks with real-world data with an unified architecture. Neural networks can replace a sequence of classical procedures with a single architecture, well suited to parallel custom implementations.

The joint optimization of neural parameters w.r.t. the error functional minimize the risk of a loss of information.

A good generalization capability of the learning algorithm is required to provide a good practical performance, especially when artificial training data is used, like in the proposed scheme.

The BRLS learning algorithm once more demonstrated its intrinsic robustness to the presence of ill-shaped regions of the error surface and was able to find quickly physically meaningful solutions to the given optimization problem.

Another distinctive element of novelty of the proposed recognition system is the character location strategy, which requires only 1-D DFT or DCT processing, together with a robust averaging of harmonic spectral peaks.

5. ACKNOWLEDGEMENT

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6. REFERENCES

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Fig. 1: Original image.

Fig. 2: Image of Fig. 1 after preprocessing and horizontal DFT.

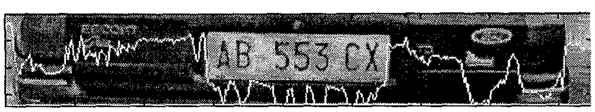

Fig. 3: Vertical DFT.

Fig. 4: Extracted plate.

Fig. 5: Character localization.

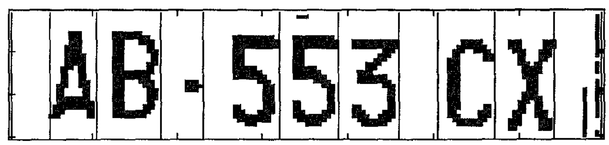

Fig. 6: Character segmentation.

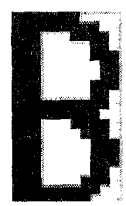

Fig. 7: Character 'B' extracted and digitized.