MULTISTAGE MORPHOLOGY-BASED LICENSE-PLATE LOCATION ALGORITHM

Tomás Brandão Tomas.Brandao@iscte.pt

Manuel Menezes de Sequeira Manuel.Sequeira@iscte.pt

Miguel Albuquerque M.S.Albuquerque@netcabo.pt

ABSTRACT

This paper describes a new license-plate location algorithm using a sequential multistage approach, where each stage consists of a different sub-algorithm. All the proposed sub-algorithms make use of morphological operations performed over both gray-scale and binary images. In order to ascertain the performance of the proposed algorithm, and to fairly compare it with license-plate location algorithms developed by other authors, a well-defined evaluation method is used. Results have shown that the proposed algorithm produces at least one accurate license-plate location hypothesis for 97.18% of 673 images acquired at a highway toll fence.

1. INTRODUCTION

In the last two decades, recognition of vehicle license-plates from digital images has assumed an important role in automatic traffic control applications, such as electronic toll collecting, finding stolen vehicles, detecting fraud and controlling access to parking lots [2].

A license-plate recognition (LPR) system can typically be divided in two main blocks organized in a cascade [1,7,10]: the license-plate location (LPL) block and the optical character recognition (OCR) block. Most systems also distinguish another block between these main blocks, whose function is to extract the characters from the located license-plate [3,8,9]. In the architecture of some systems, LPL, character extraction and OCR are all performed on a single block [6]. Throughout this document, the typical structure will be assumed (i.e., separated LPL and OCR blocks) and the character extraction block will be considered to be part of the OCR block. Nowadays, although OCR algorithms can often achieve success rates over 99% [4], the success rates of LPL algorithms are often lower, and thus are critical for the performance of the overall system [2]. This fact alone justifies more research into the LPL problem.

In this paper, a new LPL algorithm is proposed. The proposed LPL algorithm can be seen as a multistage process where each stage uses its own particular LPL algorithm. The idea is to improve the location performance of individual algorithms by combining them into a sequence of stages. In this sequence each stage attempts to locate the license-plate and, whenever it deems the results insufficiently accurate, it passes them to the next stage in the sequence. The global algorithm is also characterized by the use of morphological operations in all stages.

The algorithm was developed assuming operation in a semi-structured environment: it requires a priori knowledge about the license-plate standards (number of plate characters, dimension, *etc.*), as well as an estimate of the expected width of the plate in the image under analysis. It was also designed to be robust to poor illumination conditions. Details of the algorithm are given in Section 2.

In order to evaluate the performance of the developed algorithm, the evaluation method proposed in [5] was used. Besides evaluating the performance of the proposed LPL algorithm, the use of an evaluation method also offers the possibility of a fair comparison between the proposed algorithm and other existing algorithms described in literature. The obtained results are depicted and analyzed in Section 3. Based on this analysis, some conclusions and suggestions of future work topics are given in Section 4.

All the results shown in this paper are reproducible using Matlab software available at:

http://www.livingdata.pt/projects/SCRUARM/publicacoes/

2. DEVELOPED ALGORITHM

Given a gray-level image of a vehicle, this algorithm produces a set of hypotheses for the location of the vehicle license-plate in the image. Ideally, this set should be composed of only one of the correct hypotheses. However it is considered to be preferable to generate a small set of hypotheses in order to increase the probability that at least one of them is correct.

The algorithm assumes that the license-plate dimension and its geometric features, as well as those of its characters, are known a priori. It is also assumed that the perspective distortion of the license-plate on the captured image is small enough for these proportions to remain approximately valid.

The general structure of the algorithm is depicted in Figure 1. The algorithm can be seen as a sequence of stages, where each stage internally generates a set of possible locations. Of these, the ones that fail to comply with a priori geometric constraints in such a way that it is still possible that they contain the correct license-plate location are sent to next stage in the sequence for further processing. The location hypotheses that are considered to be good enough are added to the global algorithm's set of hypotheses. The remaining hypotheses (i.e., the ones that are too small to possibly contain the license-plate area) are discarded.

Each stage operates independently on the image regions it receives as input, which in the case of the first stage is simply the complete image. Location hypotheses are always produced as the four corners of the tightest parallelogram enveloping the corresponding image regions.

Portuguese license-plates have two possible formats: a long rectangle with 110×520 mm and a more squarish rectangle with 220×340 mm. All algorithm parameters, which were determined both using a priori knowledge and empirical tests, are expressed in terms of the expected width of the longer license-plate model, which is thus the only free parameter in the system.

2.1. Stage 1 – high contrast region detection

This stage generates a set of location hypotheses consisting of regions of pixels where the local horizontal contrast is high, since the license-plate usually consists of a set of horizontally aligned dark characters over a light background (or vice-versa).

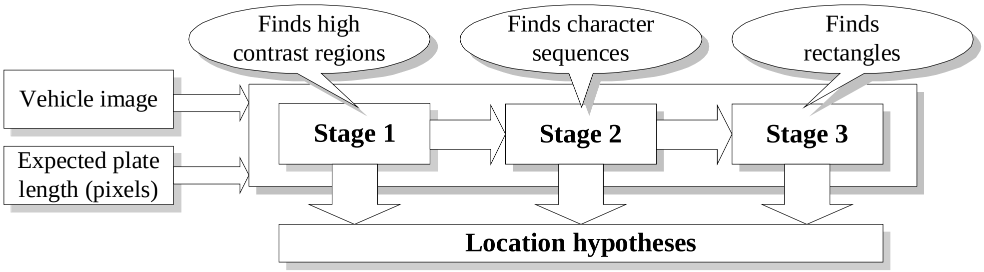

Figure 1 – General algorithm's scheme.

In order to detect high contrast regions, gray-level morphological operations over the entire gray-level image are used to produce a contrast image that will later be binarized. A two-dimensional local horizontal contrast image is obtained by computing the difference between the gray-level closing and opening of original image. The values of the contrast image are high in areas of high contrast and low in homogeneous areas. The structuring element used in the closing operation may be different from the one used in the opening. This kind of procedure is similar to the one described in [8], with the main difference that our procedure emphasizes the license-plate rectangle, instead of its characters.

In our case, the structuring elements are horizontal lines proportional to the expected license-plate width, in the case of the opening, and proportional to the maximum expected character width, in the case of the closing. The closing operation eliminates dark characters in a light background. Hence, the structuring element should be larger than the character width. The opening operation eliminates the light license-plate background, filling it with the dark tone of the characters. Hence, the structuring element should be larger than the widest expected gap between successive characters. Further morphological operations are also made in order to remove some dark regions inside the license-plate, and light regions which do not belong to the license-plate, but which nevertheless had large horizontal contrast in the original image. Figures 2(a) and 2(b) depict an example of these first steps of the algorithm.

In order to obtain the regions where the local horizontal contrast is high, the result of the previous steps of the algorithm is binarized using local thresholding, namely Niblack's method [11], since a global thresholding method would fail to detect the license-plate if other parts of the image had a higher contrast. On the other hand, using a local thresholding method will inevitably result in spurious detections. The smaller the size of Niblack's sliding window, the larger the number of spurious regions and the smaller the distance between them. A window that is too small will also lead to missing the inner part of the license-plate, which is unacceptable. On the other hand, from a computational point of view, smaller windows are better. The size and shape of the sliding window are thus very important and were empirically chosen considering these facts.

The result is a binary image with ones where local contrast is sufficiently high, as compared with nearby pixels, and zeros elsewhere. This means that the license-plate should be located in a connected region composed of ones. One way to find which regions may correspond to the license-plate is to use binary morphological operations to filter out regions whose characteristics are incompatible with the supported license-plate models. Since there are two such models, two filtering operations are run in parallel, each one specialized for a different model. The overall set of possible license-plate locations is the union of the regions resulting from each of these filtering operations that basically consist of morphological operations. The corresponding structuring elements were chosen in order to preserve the regions where it is possible to overlap a rectangle with dimensions similar to one of the real license-plates models. Figure 2(c) illustrates the binarization of the image and the subsequent results of the filtering operation for long license-plates.

The regions resulting from the two filtering operations above are then classified according to the dimensions of the corresponding bounding box. If the area of the bounding box is considered to be too small, the region is rejected. If the area of the bounding is considered to be too large, the region is considered to be a low quality hypothesis, and will be added to the set of hypotheses sent to stage 2 of the algorithm. Otherwise, the region is deemed to be a good location hypothesis and is thus added to the set of hypotheses of the algorithm's output.

2.2. Stage 2 – finding character sequences

This stage takes as input the regions that the previous stage considered to be too large, and attempts to locate horizontally aligned characters within these regions, extracted through binarization. The binarization is performed over the original gray-scale values and again using Niblack's method, this time with a rectangular sliding window proportional to the expected character dimensions.

The result of the binarization is a set of small regions consisting of sets of connected pixels. If the region being processed contains the license-plate, it is very likely that some of these small regions correspond to its characters. Thus, finding which of the small regions may correspond to characters leads to finding possible license-plate locations. Assuming that the geometrical properties of the license-plate characters are known in advance, the area, height and width of the regions are used to determine which of them correspond to possible license-plate characters. The regions that comply with the criteria are then analyzed in order to extract horizontally aligned sequences of small regions. There are several ways to achieve this goal. In our case, we used morphological operations again, namely a close operation using a horizontal line as structuring element. Figures 2(d) and 2(e) show an example of some of the algorithm steps up to and including stage 2.

The regions resulting from the closing operation above are classified, as is the case of the first stage, into discarded regions, regions which are too large and thus sent as input to stage 3, and good location hypotheses, which are added to the overall location hypotheses.

(a) Original image.


(b) Stage 1 high contrast finding.


(c) Stage 1 resulting regions.


(d) Stage 2 binarization and region removal.


(e) Stage 2 resulting regions.

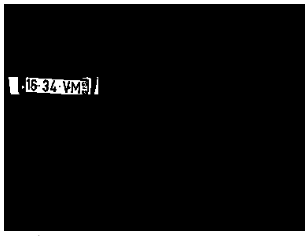
(f) Stage 3 resulting regions.

Figure 2 – Illustration of the algorithm’s processing stages.

2.3. Stage 3 – finding character sequences

Assuming that the regions entering this last stage correspond to areas that slightly exceed the license-plate dimensions, its location may be found by searching for a light rectangle within each of these regions. This can be accomplished by binarization of each region sent by stage 2, followed by a close operation in order to merge regions that belong to the license-plate but which were separated due to an erroneous binarization. The structuring element must be small in order to avoid merging with regions that do not belong to the license-plate.

After this processing step (see Figure 2(f)) those regions that are considered to be too small, applying the same criterion used in stages one and two, are simply discarded. The remaining regions are added to the algorithm's set of location hypotheses.

3. RESULTS

In order to evaluate the performance of the algorithm, several tests were carried out using the evaluation method described in [5]. The results were compared with those achieved by implementations of other algorithms found in the literature: Setchell [10], Barroso [1], Naito [9] and Martín [8]. All these algorithms require a priori knowledge of the plate dimensions. The implementation of [9] was adapted to the Portuguese case since it was originally developed to locate Japanese plates.

The input images were taken from a database of evaluation images acquired at a highway toll fence. The evaluation set has been built by randomly choosing 673 images from the whole evaluation set. This set includes vehicle images acquired at different times of the day and with different kinds of license-plate models. The algorithm was developed using the Matlab language, which is known to provide fast prototype development, but also has the drawback of leading to increased computation times. The evaluation was performed using a machine equipped with an Intel Pentium 4 processor at 3 GHz.

The results attained by the developed algorithm are given in the last column of table 1 (Brandão algorithm), together with results achieved by the competing algorithms. As can be seen from the table, the developed algorithm produced at least one correct location for 97.18% of the images, which is the best result among the tested algorithm implementations.

Taking a closer look into the failure cases, it can be observed that most of them were due to missing characters (the location hypothesis partially covered the license-plate area, but missed at least one of its characters) and spurious pixels (the location hypothesis did not miss any license-plate characters, but was considered too large). These failure cases are not the most problematic, since it may still be possible to detect missing characters given the ones successfully located, and it may also be possible to produce a more accurate license-plate location from a location hypothesis that is considered to be too large.

The proposed algorithm did not return any location hypothesis for 0.30% of the images (two images), and only in 0.15% of the images (a single image) all returned hypothesis were erroneous. The later failure case is the most relevant, since returning erroneous location hypotheses will result in useless work given to the following modules of the complete system (*e.g.* character segmentation and character recognition modules). The rate obtained by the algorithm is the lowest.

Another important feature that was evaluated is the number of location hypotheses returned by the algorithm, which should be as low as possible, since the error probability and computation time required for recognition of the plate's characters increases with the number of location hypotheses. The developed algorithm returned, in average, about 1.8 location hypotheses per image, with a maximum of 10 hypotheses in the worst case.

The average global quality attained by the developed algorithm is better than that achieved by the other algorithms. This was expected, since it also has a higher correct location ratio. However, the average quality of the first correct location is smaller than that attained by the other algorithms. The best result was obtained by Setchell's method, which produces correct location hypothesis of very high quality.

The major drawback of the proposed algorithm is the computation time required to produce the set of location hypotheses. It exhibited an average computing time of about 2.0s and a maximum computing time registered of 9.3s. The maximum computation time registered introduces some limitations to the use of this algorithm in real applications. However, it must

Evaluation Measurement	Setchell	Barroso	Naito	Martín	Brandão
Correct location	**93.16**	**87.37**	**89.00**	**93.91**	**97.18**
Spurious pixels	0.59	2.53	3.86	1.78	0.89
Characters missed	3.57	9.21	5.79	2.67	1.49
License-plate missed	0.59	0.45	0.89	1.49	0.15
No locations found	2.08	0.45	0.30	0.15	0.30
Too many hypotheses	0.00	0.00	0.15	0.00	0.00
Average number of hypotheses	2.725	2.383	1.283	2.819	1.788
Maximum number of hypotheses	9	8	15	7	7
Global quality	0.871	0.849	0.891	0.863	0.925
Quality of first correct location	0.991	0.977	0.984	0.981	0.974
Minimum time	0.234	0.734	0.296	0.750	1.281
Average time	0.605	0.960	0.481	1.157	1.897
Maximum time	1.657	1.250	2.532	1.906	10.891

Table 1 – Results attained by evaluated algorithms (rates in percentage, times in seconds).

be remembered that this evaluation refers to a prototype developed using the Matlab language. An implementation in a more efficient language, such as C++, will substantially reduce the computing time.

Other tests were also made in order to check the effectiveness of combining different algorithms using the proposed multi-stage approach. To accomplish this goal, the algorithm was evaluated using only the first stage and also using only the first two stages. From all the hypotheses returned by the algorithm, only the ones whose dimensions were considered to be too small were rejected. Running only stage 1 led to a location success of 89.15%, and thus the majority of the license-plates are located during this stage. Running the algorithm with stages 1 and 2 led to a location success of 94.21%. The overall success rate, using the three stages, is 97.18% (as mentioned before). Hence, the success rate increases 5.06% when stage 2 is appended to stage 1, and increases another 2.97% when both are appended of stage 3. It can thus be concluded that it is highly advantageous to combine different existing algorithms into a multistage algorithm.

4. CONCLUSIONS AND FUTURE WORK

A new license-plate location algorithm has been proposed. The developed algorithm is a combination of different license-plate location algorithms. It has been concluded that this kind of approach is more effective than using isolated single algorithms, since the strengths of an algorithm may compensate another algorithm's weaknesses. Evaluation results have shown a license-plate location success rate of 97.18%, using an image set consisting of 673 images.

In order to make the system more robust, some aspects of the algorithm, as well as its architecture, could be improved. Our main suggestion for future work is the introduction of a parallel multi-algorithm architecture, instead of the sequential multistage architecture proposed in this paper. This implies the development of soft decision methods in order to combine the results returned by the different algorithms. Other LPL algorithms, including the competing algorithms used in the tests, could also be adapted in order to assign them to existing algorithm's stages, or even appending new stages to comprise these algorithms.

The authors would also like to acknowledge the support of Brisa, ISCTE and Living Data.

5. REFERENCES

[1] J. Barroso, A. Rafael, E. L. Dagless, and J. Bulas-Cruz, "Number plate reading using computer vision", *IEEE International Symposium on Industrial Electronics*, vol. 3, pp. 761-766, Universidade do Minho, Guimarães, Portugal, 1997.

[2] P. T. Blythe, P. Knight, and J. Walker, "The technical and operational feasibility of automatic number-plate recognition as the primary means for road user charging", *The Journal of Navigation*, 54(3):345-353, September 2001.

[3] Y. Cui and Q. Huang, "Extracting characters of license plates from video sequences", *Machine Vision and Applications*, 10(5-6):308-320, 1998.

[4] C. de Mello and R. Lins, "A comparative study on ocr tools", *Vision Interface'99 Conference*, pp. 224-231, Trois-Rivières, Canada, 1999.

[5] M. de Sequeira, T. Brandão, and M. Albuquerque, "Evaluation of License-plate Location Algorithms", accepted for publication in the proceedings of WIAMIS 2004.

[6] S. Draghici, "A neural network based artificial vision system for license plate recognition", *International Journal of Neural Systems*, 8(1):113-126, 1997.

[7] D.-S. Gao and J. Zhou, "Car license plates detection from complex scene", *IEEE International Conference on Signal Processing*, vol. 2, pp. 1409-1414, 2000.

[8] F. Martín, M. García, and J. L. Alba" New methods for automatic reading of VLP's (vehicle license plates)", *IASTED International Conference on Signal Processing, Pattern Recognition and Applications*, Heraklion, Grece, 2002.

[9] T. Naito, T. Tsukada, K. Yamada, K. Kozuka, and S. Yamamoto, "Robust license-plate recognition method for passing vehicles under outside environment", *IEEE Transactions on Vehicular Technology*, 49(6):2309-2319, 2000.

[10] C. Setchell, *Applications of Computer Vision to Road-Traffic Monitoring*, PhD thesis, University of Bristol, Faculty of Engineering, Department of Electrical and Electronic Engineering, 1997.

[11] O. Trier and A. Jain, "Goal-directed evaluation of binarization methods" *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17(12):1191-1201, 1995.