LICENSE PLATE RECOGNITION BASED ON TEMPORAL REDUNDANCY

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ABSTRACT

Recognition of vehicle license plates is an important task in several real applications. Most approaches first detect a vehicle, locate the license plate and then recognize its characters. However, the focus relies on performing these tasks using only a single frame of each vehicle in the video. Therefore, such approaches might have their recognition rates reduced due to noise present in that particular frame. Instead of selecting a single frame to perform the recognition, we propose a novel real-time approach to automatically detect the vehicle and identify (locate/recognize) its license plate based on temporal redundancy information. To achieve further improvements, we also propose two post-processing techniques by querying a license plate database. The experimental results, performed in a dataset composed of 300 on-track vehicles acquired on an urban road, demonstrate that it is possible to improve the vehicle recognition rate in 15.3 percentage points using our proposal temporal redundancy approach. Additional 7.8 percentage points are achieved by querying registered license plates on a database by the vehicle appearance, leading to a final recognition rate of 89.6%. Furthermore, the technique is able to process 34 frames per second, which characterizes it as a real-time approach.

***Index Terms*—** automatic license plate recognition, vehicle classification, novel dataset, computer vision, machine learning

I. INTRODUCTION

Recognition of an on-road vehicle using its license plate is an important task performed by several intelligent transportation systems around the world. This task is known as Automatic License Plate Recognition (ALPR) and plays an important role in many real application scenarios such automatic toll collection, access control in private parking lots, stolen vehicles identification and traffic surveillance. Recently new approaches have been proposed to perform ALPR in an efficient way [1], [2]. However, we believe that there are still many problems that can be explored using modern techniques, e.g., simultaneous recognition of multiple vehicles and vehicle recognition in low-light environments and in high speed highways with low quality samples.

ALPR approaches are commonly subdivided into multiple smaller and simpler tasks that are executed sequentially [3]: (i) image acquisition; (ii) vehicle location; (iii) license plate detection; (iv) character segmentation; and (v) optical character recognition (OCR). Although some approaches perform vehicle tracking [4], [5], [6], they do not use all captured information to recognize the characters. Instead, they select only a single frame to perform the recognition, based on some defined rule [6], [7], making the method more sensitive to noise and prone to recognition errors.

In this work, we propose an approach to perform ALPR in real-time. One of our main concerns is to avoid the need to embedding high-cost computers on the highways. This could make the system unfeasible to be employed in the real-world applications. Although there are some works in the literature providing outstanding results in computer vision tasks using techniques based on deep learning [8], [9], [10], these are too computationally expensive and need computers with high processing power, usually provided by GPU cards. In addition, they need huge set of examples for training. Therefore, we decided to not utilize Deep Learning approaches in our ALPR system.

This work proposes a temporal redundancy approach to perform ALPR based on multiple frames instead of selecting only a single frame (see Figure 1) that can be executed in real-time. Whereas redundancy aggregation is a well-known technique in the machine learning community, to the best of our knowledge, this is the first time it is applied to improve results of an ALPR pipeline. We also develop two post-processing steps to improve the results of the recognition/identification considering that there is a database of registered license plates and vehicle models. The first is based on vehicle appearance classification (VAC) and the second is based on a search tree containing valid license plates. Finally, we introduce a public dataset of vehicles classified/labeled according to their appearance.

The main contributions of this work can be pointed as follows:

- a new real-time framework to perform ALPR using spatio-temporal information;
- two post-processing techniques to improve the final accuracy of the ALPR system;
- a public dataset of vehicles classified/labeled according to their appearance.

Our experiments were performed using a novel dataset composed of $5,200$ samples of 300 on-track vehicles acquired on an urban road in Brazil. The results demonstrate an improvement of around 15 percentage points in recognition rate when temporal redundancy information, considering the vehicle tracking is employed. Moreover, we show that we can achieve an additional increase of 7.8 percentage points when we correct the ALPR results using post-processing steps, leading to a final recognition rate of 89.6%, in contrast to 66.3%, achieved by the baseline approach.

The remainder of this paper is organized as follows. Section II reviews works related to the goal of this paper. In Section III, the proposed method using spatial-temporal approach to perform the ALPR is presented as well as post-processing steps. Then, Section IV presents the experiments conducted to evaluate the proposed approach and the achieved results are described and discussed. Finally, Section V concludes this work and discusses perspectives for future works.

II. RELATED WORK

In this section, we present a brief literature review describing some ALPR-related works. The outlined papers are divided in the following groups: vehicle detection, license plate detection, license plate character segmentation, optical character recognition, full ALPR pipeline and works addressing other car-related problems.

The preliminary tasks performed in ALPR are vehicle and license plate detection, which are usually solved using connected components labeling (CCL) [11], [12], template matching [13], background separation [14], and more often machine learning techniques [15], [16]. In the latter approach, a window is slided on the image and classified as whether containing or not a license plate (or a vehicle) according to feature descriptors extracted from each image location.

The work described in Sivaraman and Trivedi [17] compares three methods to perform vehicle detection using active learning. Furthermore, there are others important works in the field such as the one by Chen et al. [18] that proposes a new system to perform night time vehicle detection and by Kembhavi et al. [19] which proposes an approach to detect vehicles on aerial cameras using Partial Least Squares.

Since the license plate images might contain artifacts such as skew transform, shadows and blurring, generated during the image acquisition process, one of the most challenging tasks in ALPR is the character segmentation [20], [21], [22]. Araújo et al. [20] proposed a technique to segment characters using CCL and showed that the OCR results are greatly affected by the character segmentation step. For instance, while they achieved recognition rates of 95.59% for manually segmented license plates, only 71.15% was obtained when automatic segmentation was performed. Such behavior is corroborated by our current work (see Table I). The approach proposed by Soumya et al. [21] performed character segmentation by counting the black pixels in the horizontal and vertical direction of each license plate region. Finally, Wang et al. [22] employed a sequence of techniques to improve the segmentation based on vertical projection and a A* pathfinding algorithm.

The last step of the ALPR performs optical character recognition (OCR) to identify each letter and digit composing the license plate. Note that in the license plate recognition scenario, an OCR approach has to work as close as possible to the optimality (100% of recognition rate) since a single mistake may imply in an incorrect identification of the vehicle. To achieve this goal, there are works in the literature that produce outstanding results using artificial neural networks techniques [1], [11], [23] In addition, when there is prior knowledge of a specific license plate layout, the lexicon size can be diminished (for instance, plates with 4 letters and 5 digits in a sequence) and the classification accuracy can be improved. However, although most works utilizes learning-based techniques, there are also works producing promising results that use template matching to perform it [20], [24].

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Although many works propose approaches to solve only a single subtask at a time, there are also works proposing techniques to perform the entire ALPR pipeline [1], [2], [6], [25], [26], [27], [28]. The work proposed by Guo and Liu [25] detects the license plate using template matching, segments the characters using vertical and horizontal projections and recognizes Dutch license plates using Hotelling transform and Euclidean distance. The approach presented in Donoser et al. [28] utilizes analysis of Maximally Stable Extremal Region (MSER) to detect the license plate, track the vehicle and segment its characters. The characters are recognized using a SVM-based OCR. They also combine multiple detections in order to make the recognize robust to noises presented in a single frame. Wang et al. [26] proposed a technique to locate the license plate using horizontal scans of contrast changes, segment the plate using lateral histogram analysis and recognize the characters using an Artificial Neural Network for Italian license plates. Kocer and Cevik [2] proposed a work to locate the region of the image with the most transition points assuming that it corresponds to the license plate. The characters are then segmented using a blob coloring method and the characters are recognized using a multi layered perceptron. Rao [1] proposed an automatic approach to recognize vehicles in multiple cameras of a surveillance system aiming at performing the recognition in several points to estimate the vehicle path. In addition, the author described a new methods to recognize a vehicle license plate in static images by sliding window approach to detect the license plate, to counting the vertical points in the license plate region to segment the characters and to recognize them using a self-organizing neural network. Bremananth et al. [6] proposed a technique to select the best frame to recognize the license plate using a SVM trained to identify the less blurred frame. They also segment the characters using histogram analysis and recognize them using an OCR based on template matching.

Nowadays, many researchers have turned their attention to vehicle-related problems, such as vehicle classification according to a set of characteristics, other than license plate identification [27], [29], [30], [31], [32]. Shin and Wang [27] proposed a technique to recognize the vehicle using its appearance instead of the license plate characters. Dong et al. [29] presented an approach to classify vehicles into six categories: bus, microbus, minivan, SUV, sedan and truck. Their approach was able to achieve 91.6% of recognition rate using a dataset with 227 images of eight different vehicle models. Hsieh et al. [30] and Hu et al. [9] propose approaches to classify vehicles according to its color. The former applies a correction to reduce the effect of the lightning change, and the latter utilizes a deep learning technique for this purpose.

Recently, Yang et al. [32] introduced a new large dataset called CompCars containing $136,727$ car images to be used on car-related problems. The authors argue that there are still many problems that have not been well-explored by the research community, i.e. fine-grained classification and vehicle attribute prediction. In this sense, our work proposes a new approach to recognize the vehicle frontal appearance and perform a query on a dataset to reduce the domain of possible license plates. In contrast, Duan et al. [33] employed Scale Invariant Transform Feature (SIFT) and color histograms to identify characteristics of the vehicles (e.g., headlight, tire color and wheel shape), which are used then to classify the vehicles according to their model. In this work, we utilize frontal appearance to classify vehicles and improve the recognition results at the end. We also propose a novel approach to filter out unlikely license plate candidates using a simple algorithm based on a tree search.

III. Proposed Approach

This section describes the proposed improvements for license plate recognition. First, we briefly overview the ALPR pipeline (Section III-A) being employed in this work. Then, we define the proposed temporal redundancy aggregation (Section III-B) and the two post-processing techniques based on the assumption that we have access to a database containing all issued license plates (Sections III-C and III-D), e.g., a database of a Department of Motor Vehicle. Figure 1 illustrates the recognition pipeline, described in the next sections.

A. ALPR Pipeline

Vehicle and license plate detection are crucial tasks on ALPR system. We first detect the vehicle and then its license plate, located inside the vehicle patch. To solve both tasks, we employ a sliding window approach composed of a classifier based on Support Vector Machines (SVM) and Histograms of Oriented Gradient (HOG) [34] as feature descriptors. Afterwards, we track the vehicles over the multiple frames employing the approach described by Kalal et al. [35] to group temporally detections belonging to the same vehicle.

Once the license plate has been located, we need to segment the image into multiple patches containing license plate characters (LPCS). For such aim, we developed a straightforward iterative technique to perform LPCS on real scenarios. In this approach, instead of using a single threshold to perform license plate binarization using the Otsu method, we consider a set of different values. Otsu's approach assumes that the pixels of the image belong to one of the two classes: foreground and background. Therefore, it calculates the optimal threshold that separate the

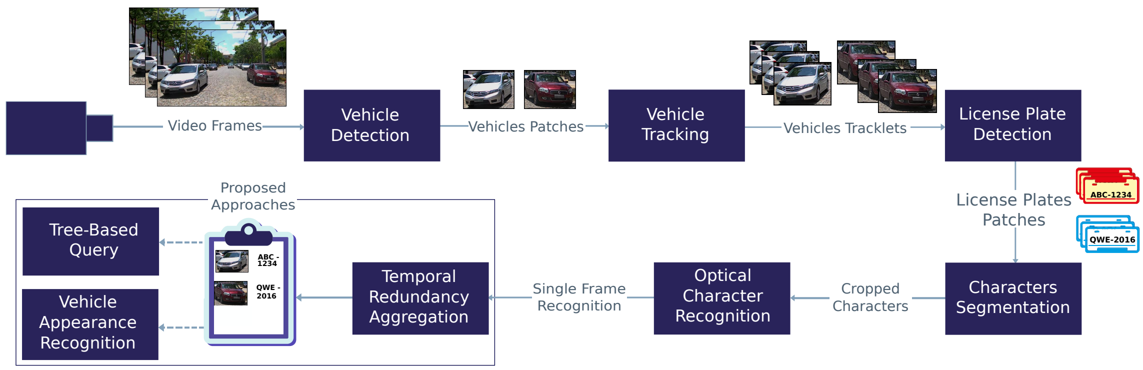

Fig. 1: Sequence of tasks performed by the ALPR. The approaches proposed in this work are highlighted in the rectangle.

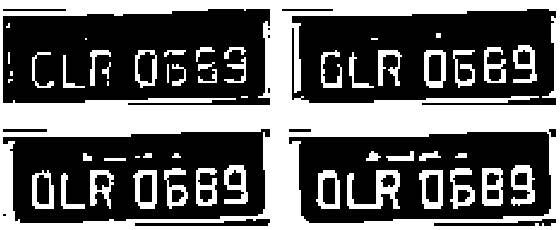

Fig. 2: Samples of the license plate considering different thresholds, 5 and 10 on the top images and 20 and 30 on the bottom images.

classes by minimizing the intra-class variance. For more details, see Gonzalez [36].

The algorithm assumes that the image contains two classes of pixels following bi-modal histogram (foreground pixels and background pixels), it then calculates the optimum threshold separating the two classes so that their combined spread (intra-class variance) is minimal Starting from a threshold equals 5, we binarize the image as we increase this threshold until we have the number of connected components equals to the number of license plate characters. Figure 2 illustrates this process. By doing this, we are trying to avoid the problem where two adjacent characters are touching each other due to noise, by some noise pixel. This could happen because a binarization starting from small thresholds tends to set most pixels to the maximum value, resulting in fewer noises connecting two adjacent characters. Note that when the threshold is too small, we tend to have more connected components due to sliced characters and when the threshold is too large, we have few connected components due to presence of touching characters.

The OCR employed is an one-against-all SVM classifier using HOG features. As a result, we have 36 trained SVMs, one for each character of the Latin alphabet and one for each digit. It is important to note that by knowing the layout of the license plate beforehand (in our case, it has three letters followed by four digits), only the appropriate models can be applied to each character (10 SVM models for digits and 26 SVM models for letters), which reduces the incorrect classification.

B. *Temporal Redundancy Aggregation*

Since the proposed approach aims at exploring the temporal redundancy information, we hypothesize that the combination of individual results belonging to the same vehicle should improve the recognition of its license plate, as illustrated in Figure 3.

We combine the individual recognition results using two main approaches: (i) majority voting and (ii) average of the classifier confidence. The use of majority voting was already employed in Donoser et al. [28]. While the former takes all predictions for each frame and assumes that the most predicted character for every license plate position is the correct, the latter averages the

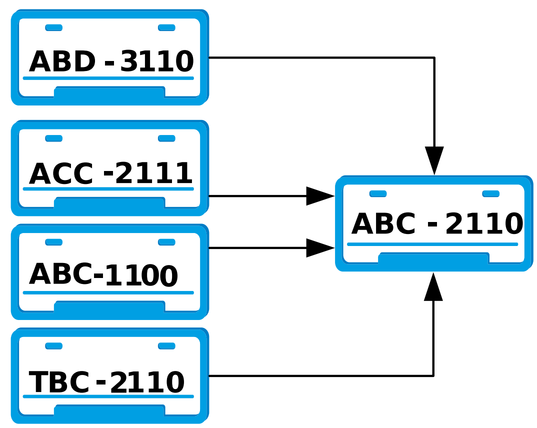

Fig. 3: The proposed approach combine results of multiple frames to improve the vehicle recognition rate.

classifier score from all recognitions and assumes that the class with the highest score is the correct. In the case of Support Vector Machines, the classifier confidence/score is given by the distance from the projected instance to the separation hyperplane, where large and small distances indicates higher and lower confidences, respectively. In preliminary experiments, we also evaluated the use of the Ranking Aggregation technique proposed by Stuart et al. [37], but the results were not satisfactory.

C. *Vehicle Appearance Classification*

Once we have the vehicle location in multiple frames, we recognize its appearance, which is used then to query the license plate database, and retrieve the license plates belonging to vehicles with that appearance. The use of vehicle appearance instead of the recognized license plate itself to select candidates can help the ALPR to discard those candidates that have license plates similar to the correct one but belong to different vehicles models. Therefore, we hypothesize that fewer candidate license plates have to be evaluated, reducing the ALPR recognition error.

The main challenge of this approach is that several vehicles from the same manufacturer might have the same frontal (or back) appearance, making the distinction of those vehicles a very complex task, even for humans (Figure 4 shows two different models that have very similar frontal appearance). Thus, we decided to classify vehicles according to their appearance instead of their actual model.

To recognize the vehicle appearance, we employ a standard recognition approach using SVM based on SIFT features and Bag of Visual Words (BoVW) [38]. The only difference between the conventional approaches and the proposed one is in the feature space quantization step of the BoVW. In this work, instead of

Fig. 4: Two different vehicle models presenting very similar frontal appearance. Voyage (left) vs. Gol (right).

creating a single global dictionary, we build a dictionary per class and append all codewords generating a large BoVW. Although this approach can generate high-dimensional feature space, it significantly improves the final recognition rate. Furthermore, since our approach considers multiple frames of each vehicle, we recognize the vehicle appearance for each frame and combine all answers using the ranking aggregation technique proposed by Stuart et al. [37].

D. Tree-Based Query

We propose this technique based on the fact that there are millions of character combinations that do not correspond to any (in-use) license plate. For instance, according to the Brazilian Department of Transportation, there are 87 million different license plates currently being used in Brazil[1]. However, the combination of three letters followed by four numbers provides more than 175 million possibilities.

Once the license plate has been recognized by the temporal redundancy ALPR, we sort the recognized characters by the OCR confidence and, from the most to the least confident character, we filter those license plates that do not have that same character on that particular position. If we find a group having only a single license plate, we assume that this is the correct license plate. Otherwise, if we do not have any license plate at some iteration, we return one level of the filtering and choose a license plate that is the most likely to the correct one using the OCR confidence.

We implement this technique using a tree. In this case, the root node contains all possible license plates and this amount is reduced at every level of the tree until convergence to a single license plate at a leaf node. The edge connecting two nodes represents the filtering of the license plate from the parent to the child by a specific character. However, it is not feasible to generate the entire tree due to its high branching factor. Instead, we can use the OCR confidence to dynamically build the tree using only the required nodes, ignoring branches with low confidence characters.

IV. Experimental Evaluation

This section presents the results achieved using the technique described in Section III. We use an approach to recognize vehicle using a single frame per vehicle as baseline to evaluate the improvement achieved by the addition of redundancy. Furthermore, this section presents the results achieved when we employ the post-processing techniques to perform vehicle appearance classification and the tree-search.

A. Datasets

We collected three sets of data to validate the proposed approaches[2]. The first set, used to train vehicle and license plate detectors, contains 650 images of on-road vehicles used as positive examples to both detectors. Figure 5 shows an example frame of this dataset. The second set, used to evaluate the entire pipeline, contains $5{,}200$ frames, with size of 1920×1080 pixels, extracted from surveillance videos with 300 on-road moving vehicles (17.33 frames per vehicle on average) recorded in Brazil. The vehicles license plates have size of 120×42 pixels and aspect ratio of 2.86 on average. The third set, used for vehicle classification by appearance, contains $1{,}000$ samples divided in 48 classes corresponding to an average of 20.83 vehicles per class. Even though we could have used the dataset proposed in Yang et al. [32], we chose to collect our own samples due to the fact that all Brazilian vehicles used in our experiments must present a corresponding appearance class within our dataset, which is not available in their data.

Fig. 5: Sample of a frame in the dataset. Each frame might have more than one vehicle.

Table I: Recognition rates achieved by the proposed approach compared to the baseline using manual and automatic character segmentation.

Approach	Segmentation	
	Manual	Automatic
Bremananth et al. [6] (without redundancy)	78.3%	66.3%
redundancy with OCR average	93.6%	77.9%
redundancy with majority voting	94.6%	81.8%

Although we developed our method using images of vehicles with Brazilian license plate models, we can also use the proposed approach on different models. For this purpose, we only have to train the license plate detector with examples of the new model and adapt the LPCS technique to work properly with the model concerned. Furthermore, in case of license plate being located in the vehicle rears, we can also train the vehicle detection to recognize the back of the vehicle using new appropriate examples.

B. Temporal Redundancy Aggregation

To evaluate the contribution of employing temporal redundancy to the ALPR pipeline, we compare our proposed approach with the technique proposed in Bremananth et al. [6]. Their method selects the best frame using a machine learning technique that classifies the frame as blurred or non-blurred assuming that the less blurred frame is, the most reliable to perform the recognition. We report the results of our approach using two techniques to combine the results: majority voting and average OCR confidence. Furthermore, we perform both automatic and manual segmentation to evaluate the influence of the character segmentation on the final recognition results.

According to the results shown in Table I, the proposed approach using automatic segmentation was able to outperform the baseline in 11.6 percentage points (p.p.) using average OCR confidence and 15.5 p.p. using majority voting. This fact corroborates the hypothesis that combining the results of multiple vehicle detections can provide better recognition rates than using just a single frame.

C. Post Processing Approaches

Once the best results were achieved using majority voting, we utilize the results of this approach as input to both post-processing techniques.

1) Vehicle Appearance Classification

To evaluate our vehicle appearance classification model, we employed a 5-fold cross-validation in the third set of images described earlier.

[1] http://www.denatran.gov.br/frota2015.htm (in Portuguese)

[2] The data used to validate the proposed methods will be made publicly available to the research community once the paper is accepted.

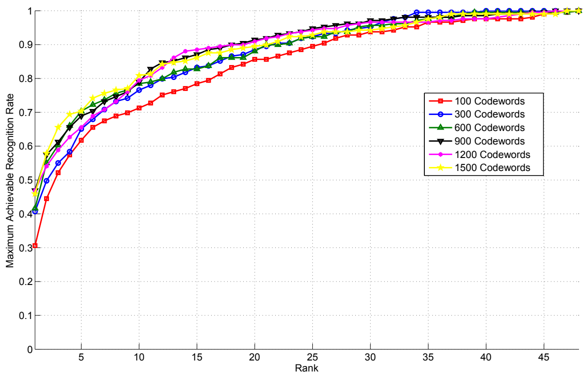

Fig. 6: Recognition rates as a function of the top rank positions.

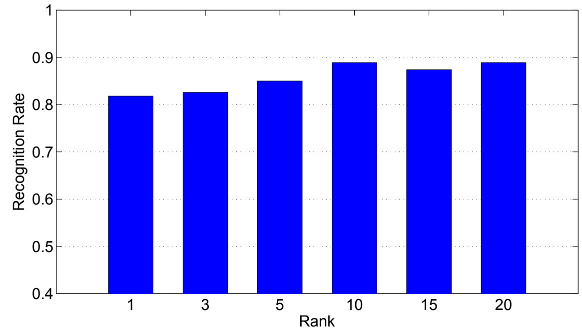

Fig. 7: Percentage of license plates correctly recognized as a function of the amount of license plates evaluated according to rank.

Figure 6 illustrates the achieved results of the proposed classifier model for different number of codewords per class. It is possible to see that there are no improvements on the classification when we use more than 900 visual words per class (final dimensionality of $43,200$). In the best case, the model was capable of predicting correctly around 48% of the test vehicle images in rank-1. Nonetheless, the model returned the correct class in 80% and 91% of the cases using ranking 10 and 20, respectively. Therefore, the use of ranks higher than 1 can reduce the search space significantly without degrading much the recognition rate. The model was capable to recognize all license plates only using the first 35 classes in the best case.

We performed an experiment varying the rank of classes used to predict the license plate, using 900 codewords per class. According to the results shown in Figure 7, the approach achieved 88.9% of recognition rate using the top 10 classes, which is an improvement of 7.1 p.p. compared to the original proposed ALPR approach, as shown in the third row of Table I (81.8%). This supports the claim that classifying a vehicle using its appearance and performing a query on a database can help to improve the ALPR results. Note that the use of more than 10 top predicted classes does not bring significant improvements to the classification.

2) Tree-Based Query

To execute the experiment using the tree-based approach, we generate a database containing 80 million random license plates to simulate a real vehicles scenario. The approach was capable of improving the results obtained using only the temporal redundancy information in 4.8 percentage points, leading to a recognition rate of 86.2%. This demonstrates that, once we have access to the database of all registered vehicles (i.e. the Department of Motor Vehicles database), we can correct erroneous recognitions, even when this database is very large.

D. Combined Results

In this last experiment, we combine the three approaches proposed in this paper. To the best of our knowledge, this is the first work applying temporal redundancy aggregation to recognize on-track vehicles. First, we recognized the vehicle combining multiple frames employing the temporal redundancy approach. Then, we performed the vehicle appearance classification to filter those candidate license plates to be used in the next step. Finally, we executed the tree-based query approach in the set of license plates filtered by the VAC model. The combined approach achieved a recognition rate of 89.6%, an increase of 7.8 p.p. compared to the results obtained considering only temporal redundancy.

E. Discussion

The proposed temporal redundancy aggregation approach was able to significantly outperform the baseline. One can observe that the use of the most reliable frame, approach proposed by Bremananth et al. [6], does not provide such high recognition rate as the combination of all images of the same vehicle does. Furthermore, although the results using manual (i.e., perfect) segmentation (Table I) are only theoretical, it is worth noticing the impact of segmentation on the ALPR system. A manual segmentation can improve the results by $12.8p.p.$ using majority voting and 15.7 p.p. using average OCR confidence, reaching a recognition rate of 94.6%.

Focusing on real-world applications, we evaluated the computational cost of our approach in a Linux Ubuntu 14.04 with 32GB of RAM and a Intel(R) Xeon(R) X5670 CPU. All techniques were implemented using the C++ language supported by the OpenCV 3.0 library. Our implementation in this scenario achieved a processing rate of 34 frames per second, i.e. the realization of a real-time system.

Both post-processing approaches were able to improve the results of the temporal redundancy approach by querying a dataset of all possible license plates. It is important to point out that the vehicle appearance classification is computationally expensive due to the high dimensionality of the feature vector. Therefore, it should be used in systems with high computational processing power, otherwise, it may compromise the ALPR system, once such system should be able to run in real-time. Furthermore, when we combined both approaches, we observed a gain of 7.8 p.p. compared to the proposed temporal redundancy approach, which is a significant improvement and justifies the combined use of both post-processing approaches.

V. Conclusions

In this work, we proposed a new approach to perform real-time ALPR exploring temporal redundancy information from detected vehicles. We also proposed two post-processing techniques to improve the final recognition accuracy of the ALPR pipeline by querying a license plate database. The former approach classifies the vehicle according to its appearance and verifies whether the recognized plate corresponds to a valid license plate of a vehicle with that appearance. The latter performs a tree-based search on the database to verify whether the recognized license plate is valid or not. Both approaches can be used by an agent/system that has access to the enrolled vehicles (their license plates) in the scenario, e.g., the Department of Motor Vehicle of a country/state. We demonstrated that we can improve the results by 15.5 p.p. using multiple frames to identify the vehicle. In addition, we showed that it is possible to achieve 89.6% of recognition rate using the both post-processing proposed approaches. As future directions, we plan to employ a Vehicle *Model* Classification trained with more classes and a larger dataset to make the filtering process more effective.

Acknowledgments

The authors would like to thank the Minas Gerais Research Foundation – FAPEMIG (Grants APQ-00567-14 and PPM-00025-

15), the Coordination for the Improvement of Higher Education Personnel – CAPES (DeepEyes Project) and the National Council for Scientific and Technological Development (Grant 307010/2014-7).

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