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Automatic Number Plate Recognition in Low Quality Videos

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***Abstract*—Typical Automatic Number Plate Recognition (ANPR) system uses high resolution cameras to acquire good quality images of the vehicles passing through. In these images, license plates are localized, characters are segmented, and recognized to determine the identity of the vehicles. However, the steps in this workflow will fail to produce expected results in low resolution images and in a less constrained environment. Thus in this work, several improvements are made to this ANPR workflow by incorporating intelligent heuristics, image processing techniques and domain knowledge to build an ANPR system that is capable of identifying vehicles even in low resolution video frames. Main advantages of our system are that it is able to operate in real-time, does not rely on special hardware, and not constrained by environmental conditions. Low quality surveillance video data acquired from a toll system is used to evaluate the performance of our system. We were able to obtain more than 90% plate level recognition accuracy. The experiments with this dataset have shown that the system is robust to variations in illumination, view point, and scale.**

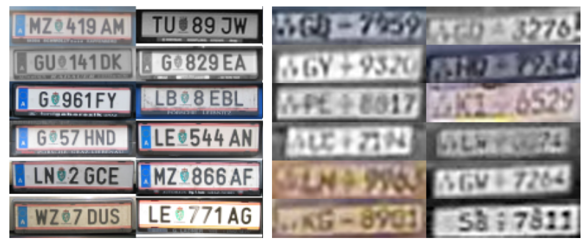
Key words - Number Plate Localization, Intelligence Transportation System, Automatic Number Plate Recognition

I. Introduction

Automatic Vehicle Identification (AVI) is the key component of the systems such as electronic toll collection systems and it could be implemented in several ways. Radio frequency identification is the most common approach, which requires each vehicle to have a RFID tag installed. Though excellent accuracy could be achieved by this method, cost of equipping each vehicle with a transponder is a disadvantage.

Automatic Number Plate Recognition (ANPR) is an alternate approach, which uses the smart cameras installed at the interchanges to capture the images of the vehicles passing through. In these images license plates will be localized and then Optical Character Recognition (OCR) will be used to recognize the license plate. Current ANPR systems mostly rely on special hardware like high resolution cameras or infrared sensors to acquire good quality images and they operate under rather restrictive constraints.

However, still, most of the toll systems do not use advanced cameras, instead they use already installed low resolution surveillance cameras and those systems do not have much control over the environment. Thus, in this work, we developed a fully-fledged ANPR system that is able to identify the vehicles even in low resolution images. We have made least-level of assumptions about the environmental conditions and utilized regular hardware resources in developing our system. In order to evaluate the performance of our system we utilized a low quality video dataset acquired from the surveillance cameras installed in a toll system.



(a) (b)

Fig. 1. Comparison between (a) the license plate images acquired using high quality cameras of a typical ANPR system, and (b) the license plate images acquired from CCTV cameras, which we are dealing with in this work.

Fig. 2. Sample images captured by the surveillance cameras, subject to illumination changes, viewpoint variation, head light impact and heavy distortion.

In Figure 1, we have compared the license plates extracted from a typical ANPR dataset acquired using high resolution cameras, and the license plates extracted from the poor quality dataset that we are dealing with in this work. By simple visual inspection it is evident that even for normal human eyes it is very difficult to identify the license plates in our dataset.

In Figure 2, typical images of our dataset obtained at different daytime and weather conditions are presented. From these images it is evident that the recognition ability is heavily affected by the illumination changes, and the license plates are

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subjected to view point variations. Moreover, these images are heavily distorted.

These figures illustrate the poor quality of the data we are dealing with and the complexity of the recognition task. Since typical ANPR steps fail to produce preferred results in this dataset, we made several improvements to the existing methods, and incorporated intelligent algorithms, and domain knowledge to improve the accuracy. The experiments with above low quality dataset have shown that the system is robust and invariant to illumination, view point variation and scale. And it is also ensured that the system operates in real-time, i.e., it does not miss any vehicles passing through the toll gates.

The paper is organized as follows: the next section constitutes a review of related work. In section 3, our ANPR system is described, followed by the experimental results and performance of the system which are presented in section 4. In section 5, our approach is compared with some other related works.

II. Related Work

Like any other vision problem, automatic number plate recognition (ANPR) heavily depends on the input image quality and most approaches work on constrained environments that provide good image quality, fixed illumination, fixed viewpoint and limited vehicle speed. Under these assumptions the state-of-the-art solutions [1], [12] give very good accuracy (>95%) in real-time (>20fps). Typical ANPR system consists of three major components - license plate localization, character segmentation and character recognition.

Localization methods can be categorized as region-based methods and learning based methods. Region based methods include Maximally Stable External Region (MSER) approach [2], [13] and use of vertical and horizontal scan lines approach for text detection. For low quality images these methods do not give satisfactory results. This leads us to consider learning based methods using classifiers such as Adaboost, SVM etc. Impressed by the results of Arth et al. [1], we used the novel framework proposed by Viola and Jones [10], originally for real-time face detection, for plate localization.

State-of-the-art segmentation methods uses connected component analysis (region growing) and verify the results using the license plate syntax (character placement, char size etc.) [6], [11]. Region growing requires hard boundary between two connected components and due to the low image quality, the hard boundary may not exist. This results in adjacent characters merging into a single connected component.

Recognition is a multiclass classification problem and several methods are available such as template matching [8], SVM [9], and decision tree (create the tree based on grouping confusing chars). Since the image quality is low, we need the classifier to learn the variations and we require fast detection. Therefore we go for SVM which is known for its efficient running time and proven performance in the ANPR domain [1], [2].

The MSER based license plate localization, proposed by Donoser et al. [2], does not perform well in our low quality images. Our approach is very similar to Arth et al. [1], which uses Adaboost cascaded classifier for plate localization, Kalman filter for tracking, and SVM for character classification. However, their approach produces poor results in unconstraint environments where illumination and view point changes are inevitable. Matas and Zimmermann [7] proposed a different approach for number plate recognition which is based on Category-Specific Extremal Region (CSER) detection. Although this approach produces very good recognition rates even in unconstraint environments, their algorithm suffers from high computational time (1.1s for 640x480 image), which is not suitable for real-time systems.

In all the above mentioned works license plates are easily readable by humans, whereas our dataset images are heavily distorted. This increases the complexity of the recognition task, making it difficult even for humans. The main contribution of this paper is a novel real-time framework for unconstrained (viewpoint invariant, illumination invariant) license plate detection, tracking and recognition in low quality (highly distorted) video sequences. In our approach we try to concentrate more processing power on important areas, through methods such as the use of a cascaded classifier for plate localization, and estimating possible plate regions using Kalman tracker. These enable us to achieve real-time performance.

III. System overview

The system consists of four modules: license plate localization, post-processing and verification, plate tracking and plate character recognition. System localizes newly appearing license plates based upon the framework proposed by Viola and Jones [10]. After detection, the results are verified. Verified plates are then fed to the tracking module which tracks the consecutive plates of a particular vehicle and also differentiates two vehicles within the scene; the tracker output will consist of multiple plate representations for each real license plate. Finally for each plate representation, characters are segmented, labels are assigned by trained SVM classifier and the recognition results are combined to improve accuracy.

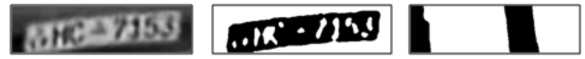
A. License plate localization

License plate localization is based upon the framework proposed by Viola and Jones [10]. The framework combines AdaBoost algorithm [3] with Haar-like features and cascade of classifiers ensures more processing power invested on positive patches; enables real-time detection.

Generally, a license plate has two characteristics: dark characters in bright background and dark rectangular border. Viola and Jones detector with Haar-like features inherently exploits dark regions in bright background to localize the license plate. Hence, the localizer can be "cheated" with similar non-license plate regions, which results in false alarms. A typical localization result is depicted in Figure 3. The dark rectangular border is exploited in the next module to verify the plate.

Fig. 3. Result of applying AdaBoost algorithm with Haar-like features in our dataset for license plate localization.

(a) Grayscale conversion



(b) Threshold and Invertion

(c) Cropping out unwanted region

(d) Rotation

(e) Again cropping out unwanted region

Fig. 4. Middle and right columns depict the results of applying post processing steps on an actual license plate and a false alarm respectively, whereas the left column represents the plate preparation for the following stages.

B. Post-processing and verification

The module incorporates simple image processing and machine learning techniques and license plate characteristics to verify the localization results and prepares the plate for character recognition. Here, a copy of the plate is kept untouched to avoid any information loss due to post-processing.

First, thresholding (inverted) with threshold 128 and morphological opening are applied. This enhances the plate region and may distort the characters. Then, unwanted regions are cropped out by scanning horizontally and vertically. Then, only the plate region will remain but they may be rotated with respect to z-axis (viewpoint may vary). Lines corresponding to the top and bottom borders of the plate are identified using linear regression and the plate is rotated based on the average gradient (finding only the top gradient may be enough, but average gradient improves robustness); thus viewpoint invariance is achieved. Once again unwanted regions are cropped out to ensure only the rectangular plate region is available to the following stages. The intermediate results are shown in Figure 4.

Because the license plate is a rectangular region, a lower bound for the aspect ratio (width/height) is used to correctly identify the plate; in our case it is 3.6. This is the approximate width-to-height ratio of the license plate category to be detected. Only the actual plates will pass through the test and this module outputs the gray scale image with only the cropping and rotation applied.

C. Plate tracking

As the system is getting a continuous sequence of frames, it needs to track the plates corresponding to a particular vehicle and it should be able to differentiate two vehicles within a scene. On the other hand, the tracker also estimates subsequent plate positions to reduce the region of interest to search for the next plate. This improves the speed and accuracy of the overall system.

The tracker is implemented as a state machine using the Kalman filter [5] as depicted in Figure 5. Initially it observes the license plates to find the initial license plate center and tracks consecutive plates. Upon significant displacement in the plate center, it hands over the tracked plates to next module and initiates a new plate to be tracked.

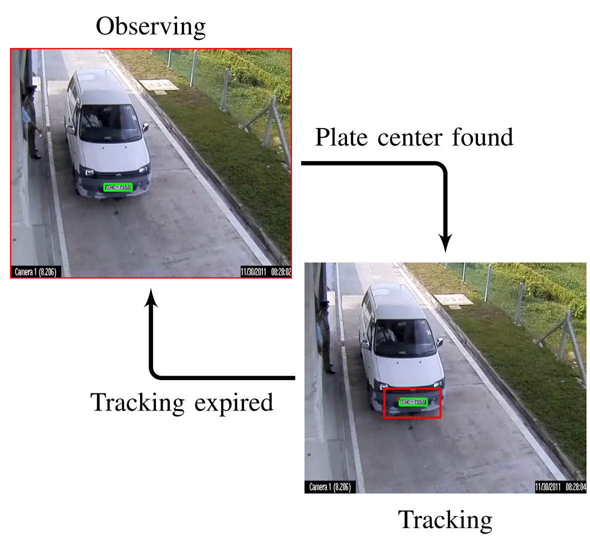


Fig. 5. Finite state machine for license plate tracking, which consists of two states - observing and tracking. In the observing state the initial license plate center will be found, with full image as Region of Interest (ROI) and in the tracking state that center will be tracked, with reduced ROI.

D. Plate character recognition

The structure of plate character recognition module is depicted in Figure 7. It gets multiple representations for a particular license plate from tracking module to make a confident recognition.

The characters are segmented by incorporating character placement information of the license plate. Here, usual connected component analysis fails 6 due to the poor image quality; they tend to merge two characters and cannot be generalized. The input images are properly prepared in section 2.2, which ensures robust segmentation results. As the license plates have a character placement format (may differ worldwide), the system can be adapted to a particular format of license plates by configuring the format.

Fig. 6. Result of applying connected component analysis on the verified license plate.

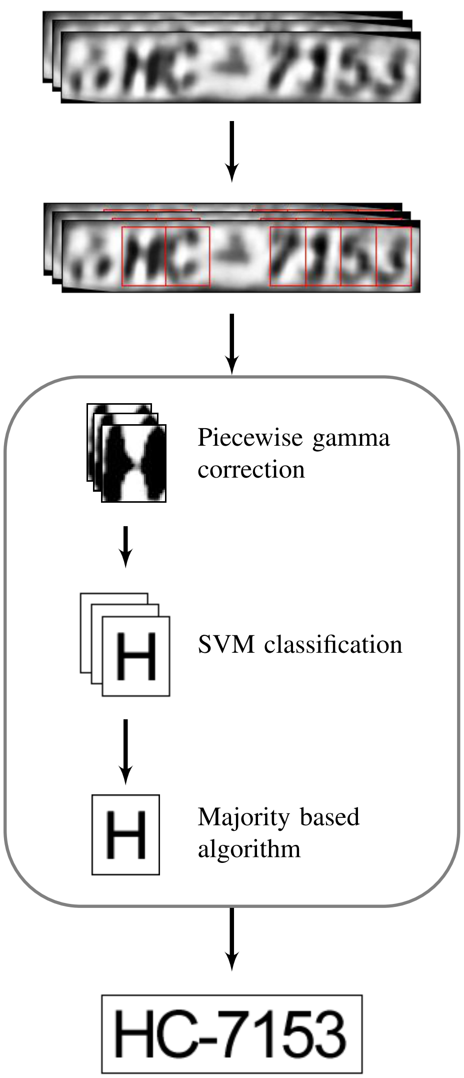


Fig. 7. Flowchart of the plate recognition module which takes multiple representation of a plate as input to make confident prediction.

Piecewise gamma correction [4] is applied to each character to ensure illumination invariance, which has the following form:

$$f(p) = \begin{cases} 0, & \text{if } p < lb \\ 1, & \text{if } p > ub \\ p^{\gamma}, & \text{otherwise} \end{cases}$$

This is done for each pixel p, with the lower bound $lb = 0.4$, upper bound $ub = 0.6$ and gamma $\gamma = 2.5$.

SVM is used for character classification. Segmented characters are resized to a common patch size (alphabets and digits are treated differently as they have different aspect ratios in the plate) and normalized pixel values are used as features. Since character classification is a multi-class problem, two multi-class classifiers with probabilistic output are trained, one for alphabets and the other for digits. This eliminates the confusion between alphabets and digits. Radial Basis Functions (RBFs) are used as kernels and optimum values for the parameters C (regularization parameter) and γ are found by cross-validation.

For each character the classifier outputs a list of labels and corresponding detection probabilities. First mode and second mode of the detection results are checked for "competition". The "competition" can be evaluated by the formula $(n_1 - n_2) <= 0.4 * N$ where n_1, n_2 are frequencies of first & second mode and N is the no. of plates used. If there is a "competition" the label with larger average detection probability is chosen, otherwise the label associated with the first mode is chosen.

IV. System Analysis

Our system is tested with a low quality video dataset acquired from the surveillance cameras mounted at the interchanges of an expressway. Here the vehicle are moving in a single lane at residential speed and the camera is fixed above. The frame resolution is 704×576. The poor quality of the camera for license plate recognition, illumination and viewpoint variations make this a challenging dataset to test our system. Our results are summarized below.

A. Results

As shown in Table I, every module tries to improve the precision while maintaining the recall, and performs the assigned tasks effectively.

TABLE I
For license plate detection, with the inclusion of each module in the given order the recall is maintained at 98% while precision is improved from 75% to 99%.

Inclusion of module	Recall	Precision
License plate localization	98%	75%
Post-processing and verification	98%	85%
Plate tracking	98%	99%

Localizer detects the text-like regions (dark pattern in bright background) which did not exploit the feature rectangular border. Therefore the localizer gets "cheated" by false similar dark patterns. Although it has many false plate detections,

TABLE III
COMPARISON OF RELATED WORK WITH OUR APPROACH. EVENTHOUGH OUR SYSTEM OPERATES ON HIGH RESOLUTION IMAGES, THE IMAGE QUALITY IS LOW DUE TO CAPTURE ENVIRONMENT AS DEPICTED IN FIGURE 1

Criteria	**Donoser et al. [2]**	**Arth et al. [1]**	**Matas et al. [7]**	**Ours**
Image Quality	Human readable	Human readable	Human readable	Hardly readable
Viewpoint Invariant	No	No	Yes	Yes
Illumination Invariant	To some extent	To some extent	Yes	Yes
Performance	∼11fps for 352x288 image	∼20fps for 352x288 image	∼1fps for 640x480 image	∼25fps for 704x576 image
Character level accuracy	∼97%	∼98%	∼98%	∼98%
Plate level accuracy	∼95%	∼96%	∼95%	∼90%

TABLE II
SUMMARY OF THE AVERAGE RUNNING TIME OF EACH MODULE PER FRAME.

Module	**Average running time / frame (ms)**
License plate localization	4
Post-processing and verification	20
Plate tracking	0.2
Plate character recognition	14
Overall system	38.2

localizer does not miss any true license plates. The verification module discards most of the false detections without affecting the true detections by checking the aspect ratio of plate candidates. Tracker estimates the dynamic ROI which allows the algorithm to confidently specify a smaller ROI where the plate of the same vehicle should be detected in the next frame, if one exists. Hence, it reduces the confusion of the localizer which improves the precision of the system by a great margin.

Recognition rate is improved with the use of multiple plate representations for character recognition and our system is able to achieve 90% plate level accuracy with character level accuracy of 98% for 40 plate representations of a single vehicle. Character level accuracy of the system is close to the ideal as expected; since SVM classifier is combined with the majority algorithm. However, the plate level accuracy is little low, due to the fact that a plate recognition will go wrong even if a single character is wrong. Figure 8 depicts the relationship of plate level accuracy with number of plates used for recognition.

B. Performance

The average running time per frame for each module is summarized in Table II. The performance of the localizer is heavily dependent on the size of the ROI it is searching for. Our algorithm try to reduce the ROI once the plate is confidently detected, and it is able to localize a plate within 4 ms. Verifier performance heavily depends on the linear regression algorithm that is used to achieve viewpoint invariance. Even though it is costly, it cannot be avoided because unless horizontal alignment of the plate is precise, character recognition will be making the full system useless. Plate tracking is based on the Kalman filter which is very efficient for 2-dimensional space. The costly processing in character recognition module is the SVM classification and it needs to classify at-least 40 plates to get 90% accuracy. If

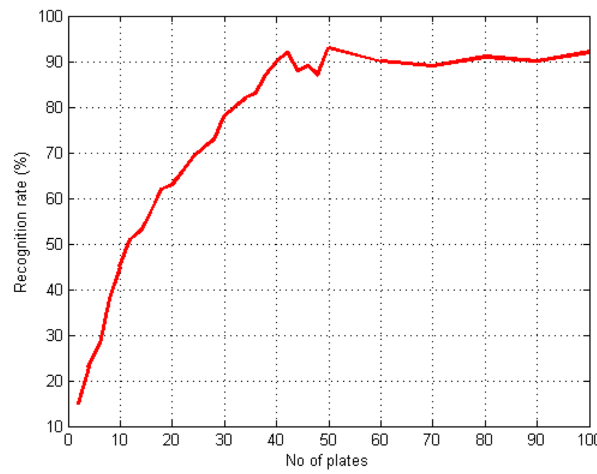


Fig. 8. Plot of overall plate recognition rate against the number of plate instances per plate used in the plate recognition module.

the system performs the classification collectively at once, it will take approximately 600 ms and it might miss a vehicle. Therefore our system classifies each plate immediately and performs the majority algorithm once per vehicle. Hence our system is able to achieve real-time performance (25 frames/s) with 90% recognition rate.

In Table III our approach is compared with related works with respect to results, performance, invariance operation and complexity of recognition task. From this comparison it is evident that our approach is a robust, illumination invariant, viewpoint invariant and real-time solution for automatic number plate recognition even in low quality videos.

V. CONCLUSION

In this paper we proposed a real-time, robust license plate recognition algorithm which works with videos taken with regular cameras. We use Viola-Jones for licence plate localization along with the Kalman filter, which enables us to concentrate processing power on promising regions. We use SVM in a majority voting framework across multiple detections of a plate for character recognition. Our system achieves 90% recognition rate in a data set which is even imperceptible for human. Our algorithm surpasses existing ones in terms of the performance in low-resolution videos and invariance. Its recognition rate is marginally inferior or on par with existing systems.

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