End-to-End High Accuracy License Plate Recognition Based on Depthwise Separable Convolution Networks

Song-Ren Wang, Hong-Yang Shih, Zheng-Yi Shen, and Wen-Kai Tai
Computer Science and Information Engineering
National Taiwan University of Science and Technology
Taipei, Taiwan
Email: {B10415005, B10415045, M10715098, wktai}@mail.ntust.edu.tw

Abstract—Automatic license plate recognition plays a crucial role in modern transportation systems such as for traffic monitoring and vehicle violation detection. In real-world scenarios, license plate recognition still faces many challenges and is impaired by unpredictable interference such as weather or lighting conditions. Many machine learning based ALPR solutions have been proposed to solve such challenges in recent years. However, most are not convincing, either because their results are evaluated on small or simple datasets that lack diverse surroundings, or because they require powerful hardware to achieve a reasonable frames-per-second in real-world applications. In this paper, we propose a novel segmentation-free framework for license plate recognition and introduce NP-ALPR, a diverse and challenging dataset which resembles real-world scenarios. The proposed network model consists of the latest deep learning methods and state-of-the-art ideas, and benefits from a novel network architecture. It achieves higher accuracy with lower computational requirements than previous works. We evaluate the effectiveness of the proposed method on three different datasets and show a recognition accuracy of over 99% and over 70 fps, demonstrating that our method is not only robust but also computationally efficient.

I. INTRODUCTION

Automatic license plate recognition (ALPR) is an essential part of research for intelligent transportation systems such as surveillance systems for access control, traffic monitoring, traffic violation detection, and parking lot management.

Despite the large body of approaches proposed for ALPR [1]–[7], challenges still exist in real-world applications. For example, highly distorted or blurred vehicle images, poor lighting conditions, and frigid weather conditions all significantly influence the recognition process. As most previous solutions rely on extra rules (e.g., the maximum number of characters allowed in a plate) to enhance their accuracy, or validate their methods on datasets that are environment-specific (images are collected using a single camera or from identical viewing angles), or lack diversity (for instance, they recognize only a single class of vehicles or plates with the same background color), they perform well only in restricted scenarios. A robust ALPR system, however, should address these common challenges and adapt to diverse environmental conditions.

Traditional license plate recognition (LPR) methods are commonly based on segmentation-based methods, that is, character detection followed by character recognition. Such methods require accurate character segmentation: faults in segmentation lead to misrecognition of license plates even when using a robust character recognizer. However, in real-world scenarios, as blurry images and environmental factors degrade the accuracy of character segmentation, these methods are not suitable for real-world applications; moreover, separating character detection and recognition brings with it additional computational costs. With the development of deep learning techniques, more and more innovative ideas for solving LPR without character segmentation have been proposed [4], [8], [9]. Segmentation-free methods usually extract features from license plates and deliver them to a CNN or RNN model to recognize the character sequence. Practically, these methods have better performance and accuracy and are more robust, compared to segmentation-based methods.

In this paper, we propose a novel segmentation-free neural network architecture for LPR based on Xception [10] and Inception-ResNet v2 [11]. With the deep learning infrastructure provided by both, the network learning is deeper and requires fewer parameters; that is, it is efficient and fast, compared to other machine learning methods. In addition, we integrate an affine transformation model into the proposed recognition system to rectify distorted images before they are submitted to the recognition model. Several datasets are used to verify the proposed method, showing that it achieves 99% accuracy with an average fps (frames per second) of over 75, indicating that it is applicable under different environments and challenging conditions without any implementation change.

Apart from using public datasets [1], [5], [8] to validate the proposed method, we also describe NP-ALPR [12], another large dataset with over 10,000 vehicle images recorded from several cameras under various conditions, including locations, vehicle distance, lighting conditions, and times of day. Furthermore,

1Due to local privacy policies, we cannot make NP-ALPR publicly available. For access to NP-ALPR, please contact the first author.
this dataset contains various types of vehicles (motorcycles, cars, buses, and trucks), license plates with various background colors (white, green, yellow, and red), and license plates with characters in various colors (black, white, and red). Examples of the dataset are shown in Figure 1. Note that the dataset also includes images with multiple vehicles in the same frame.

To summarize, the main contributions made by this work are as follows:

- We propose a novel end-to-end LPR model without character segmentation based on Xception and Inception ResNet v2.
- The proposed LPR method recognizes license plate characters at 99% accuracy and over 75 fps under different datasets, confirming that it is robust enough to be applied in real-world applications and that it outperforms several recent works.
- We present NP-ALPR, a dataset that contains over 10,000 images of various types of vehicles under various conditions.

In the next sections, we first discuss approaches raised in recent years to recognize license plates and then present the network architecture and training flow of the proposed method. We then present the experimental results to verify the proposed method.

II. RELATED WORK

Common methods for LPR can be divided into segmentation-based and segmentation-free methods. In this section, we briefly review recent work on both LPR methods and present a brief description of work that our research touches upon. Since this work mainly focuses on LPR, we do not include studies on vehicle and license plate detection.

A. Segmentation-based LPR

Most conventional LPR methods perform character detection first and then recognize the segmented character (character recognition). Several recent works [5]–[7] are based on this methodology and differ only in implementation details.

Existing algorithms for character detection can be classified into two groups, the first based on connected component techniques that build connected areas from binarized images and regard each as a character [2], [12], [13], and the other based on projection techniques that separate each character according to the top/bottom boundaries obtained from a horizontal projection of binarized images [7], [12], [14].

Various algorithms have been proposed for character recognition which are based either on template matching or on machine learning methods. The former has been used widely for character recognition by measuring the similarity between the segmented character and template images [14]–[16]. For the latter, [17], [18] proposed works that apply a scale-invariant feature transform (SIFT) [19] to extract features from segmented characters for delivery to support vector machines (SVMs) [20] for final classification. As this method requires numerous sliding windows to extract license plate features, however, it is more computationally costly. The regional convolutional neural network (RCNN) avoids such unnecessary computations by using selective search to optimize the detection, but it requires more effort to train the models. Other common machine learning methods include probabilistic neural networks (PNNs), hidden Markov models (HMMs), and multilayer perceptrons (MLPs).

B. Segmentation-free LPR method

Solutions for LPR without character detection emerged following advances in machine learning and deep learning. Elimination of character detection enables these approaches
to achieve better performance relative to segmentation-based methods. [13] propose the first segmentation-free LPR method by using convolutional neural networks (CNNs). LP image features are extracted via CNNs, and a recurrent neural network (RNN) with connectionist temporal classification (CTC) is used to label the sequential data and to classify the character sequence. Similar CNN-based work includes [4], [8], [21].

To the best of our knowledge, [9] proposed the first work to use advanced semantic segmentation for license plate recognition based on a modified version of DeepLabv2 ResNet-101. This method is based on pixel-wise classification, which usually yields more robust accuracy but is more computationally complex. It achieved outstanding results on the AOLP dataset [1].

C. Datasets for ALPR

The SSIG SegPlate Database [22], which contains 2k Brazilian license plate images, is a commonly used benchmark for ALPR research, but as the images were collected only on sunny days and from a static camera with monotonous backgrounds, the data is neither representative nor convincing. The UFPR-ALPR dataset [5] contains 4.5k images of different types of vehicles captured by three different cameras, yet does not include variations such as daytime differences and weather conditions. The AOLP dataset [1] contains three subsets: Access Control (with 681 images), Traffic Law Enforcement (with 528 images), and Road Patrol (with 611 images). Although each subset contains images under different conditions, such as various times of day, tilted plates, and different viewing points, the total number of images is relatively small. In [8], the author proposes the Reid dataset, which contains 76k license plates. Although it contains a large number of images of license plates, it lacks variations in tilt angles. To the best of our knowledge, [23] propose CCPD, the largest-yet dataset, with over 250k unique car images in China with detailed annotations under diverse environmental conditions.

III. PROPOSED METHOD

In this section, we present the architectural overview and data flow of the entire network, and also describe the training process and provide implementation details.

### TABLE I

| Layer                      | Input/Parameter          | Output         |
|----------------------------|--------------------------|----------------|
| Concat (128, 32), (128, 32) | (128, 32, 2)            |                |
| Conv + BN + LeakyReLU (128, 32, 2) | (64, 16, 32)         | (64, 16, 32)  |
| Xception Module (64, 16, 64) | (64, 16, 64)           | (64, 16, 64)  |
| Inception Module B (64, 16, 64) | (64, 16, 64)        | (64, 16, 64)  |
| Xception Module B (64, 16, 64) | (64, 16, 64)          | (64, 16, 64)  |
| Xception Reduce Module (32, 8, 128) | (32, 8, 128)    | (32, 8, 128)  |
| Xception Module B (32, 8, 128) | (32, 8, 128)         | (32, 8, 128)  |
| LSTM (32, 128)               |                         | (32, 38)      |

### TABLE II

| LP with 4 characters | LP with 5 characters | LP with 6 characters | LP with 7 characters |
|----------------------|----------------------|----------------------|----------------------|
| AA-AN                | AA-ANN               | AA-NNNN              | AAA-NNNN             |
| AA-NN                | AA-NNNN             | AA-NNNN             | AAA-NNNN             |
| AN-NN                | AN-NNN              | NA-NNN              | AAA-NNN              |
| NA-NN                | NA-NNN              | AAA-NNN             | AAA-NNN              |
| NN-AA                | NNN-AA              | AAN-NN              | AAA-NNN              |
| NN-AN                | NNN-AN              | ANA-NN              | AAA-NNN              |
| NN-NA                | NNN-NA              | ANN-NN              | AAA-NNN              |
|                     |                      | NNN-NN              | NNN-NN               |

A. Overview

The main purpose of this work is to introduce a real-time and highly accurate license plate recognition method. Unlike segmentation-based methods which require character segmentation followed by character recognition to predict the license character sequence, the proposed model processes the whole license plate image without segmentation. We also use CTC loss for segmentation-free training so that we do not need to annotate the positions of characters in license plates. Here RGB license plate images cropped from raw images are considered as the inputs for the model rather than the raw images with vehicles and other background material. Practically, this is easily accomplished with various detection solutions. For example, previous work [5] uses YOLOv2 [24] or the latest YOLOv3 [25] as the license plate detector and vehicle detector. In this work, we simply use YOLOv3 as a license plate detector in several experiments that require

![Fig. 2. Dataset augmentation generated by imgaug library with different settings. The left-top image is the raw image.](image-url)
license plate detection. Since this work mainly focuses on license plate recognition, details on detection methods are not presented here.

Existing powerful networks such as AlexNet, VGGNet, or GoogLeNet are widely popular in recent work. However, to build a fast and lightweight network, wholesale use of these monolithic networks is not the best option. In this work, the basic building blocks of the proposed networks were inspired either by Inception ResNet v2 [11] or Xception [10], or both. The Inception network is a deep neural network that achieves outstanding performance with a modest number of parameters; due to its complicated design, however, it is still too computationally costly for use in license plate recognition applications. In [11], improved versions of Inception with residual connections prevent vanishing gradients; that is, Inception ResNet v1 and v2 achieve slightly better performance than their predecessors. On the other hand, the Xception network, although not as powerful as the former, benefits from the adoption of depthwise separable convolution and is thus significantly more efficient and requires fewer parameters to match the performance of the former. To strike a good balance between accuracy and computational efficiency, we make use of portions of both to construct a license plate recognition-specific network rather than directly use both heavy networks. The building blocks used to construct license plate recognition model are illustrated in Figure 2. Note that in the original works [10], [11], few implementation details are given, and ReLU is used for activation in both works. However, in several experiments, we found that replacing ReLU with LeakyReLU improved overall efficiency. Hence in this work we use LeakyReLU as the activation function.

B. Affine Transformation Module

Tilted license plate images are common in real-world scenarios and often lead to inaccurate prediction. To take this into account, we correct the tilt of input images before the license plate recognition phase. To rectify tilted license plate images, we apply affine transformation to un warp them, so that in the license plate recognition phase, every license plate resembles one captured from the frontal view. To precisely un warp distorted license plate images, we train an affine transformation model to capture the license plate’s four endpoints and deliver them to the correction algorithm. We experimented with several affine transformation algorithms, and found the one provided by the OpenCV library to be more stable than others. Thus we adopted it in our implementation. Figure 4 shows the detailed architecture of the affine transformation model. The results show that the affine transform model yields a roughly 1 to 3 percent increase in recognition accuracy.

C. License Plate Recognition Module

The network architecture of the proposed segmentation-free license plate recognition model is presented in Figure 4. To begin with, image features are extracted using a pre-trained CNN model that slides across a license plate bounding box with an input size of 128 × 32, and principal component analysis (PCA) is applied to reduce the feature dimensions, yielding feature maps of size 32 × 8, which are then delivered to the DNN model with a bidirectional CudnnLSTM layer followed by a fully connected layer to obtain sequential features. Lastly, CTC is applied to decode the sequential LSTM features and to predict the character sequence. The parameters of the network architecture are shown in Table 1.

During the experiments, we observed that although higher input sizes yielded more accurate results, we found that 128 × 32 is the best choice for the network as a trade-off between accuracy and performance. To increase efficiency, we also attempted to reduce the feature map size to 16 × 4, but this led to significantly inaccurate results.

D. Model Training

Accurate prediction usually requires model training on a large number of samples. However, existing datasets are commonly small-scale and thus do not satisfy this requirement. To take this into account, we first trained our model using an autoencoder, an unsupervised learning algorithm that allows the model be trained on only a few labeled samples, after which transfer learning is using to enhance the model. Secondly, we made use of the imgaug library to augment the training samples by generating blurred and distorted images. Examples produced by the imgaug library are shown in Figure 2. Further, because some license plate letters are relatively infrequent in our region (for example, I and O), we synthesized infrequent characters to produce fabricated license plate images and used them to train the model. To do so, we first randomly chose segregated characters cropped from the dataset, and then measured the similarity between the currently selected character and the partly completed license plate to determine whether the character should be kept or discarded. To make the fabricated license plate resemble a real one, we followed all legal rules of character combinations of license plates shown in Table 1 to fabricate license plates. The experiment results showed that fabricated samples have a character distribution similar to real license plates, and that they benefit not only accuracy for license plates with infrequent characters but also overall performance.

IV. Experiment

In this section, we present our experimental results on the AOLP dataset, the UFPR-ALPR dataset, and our own NP dataset. Although the CCPD dataset includes a huge number of license plate images, because non-ASCII characters are used to represent the province code, we did not evaluate on this dataset as our model currently does not support non-ASCII characters. Here we consider both recognition accuracy and running time as performance metrics and provide several comparisons with state-of-the-art methods.

All of our models were trained using an NVIDIA GeForce RTX 2080 Ti with specific images provided by each dataset; testing was conducted on a GTX 1070.
Fig. 3. Implementation details of Xception and Inception building blocks originally proposed in [10], [11]. As names of these building blocks were not given, we name them according to their functionalities. Also, we adopt LeakyReLU as the activation function, whereas in the original work they did not reveal the implementation details.

Fig. 4. Detailed overview of proposed neural network architecture, including affine transformation model and license plate recognition model.
### Table III: AOLP Results

|         | AC (%) | LE (%) | RP (%) | Avg (%) | fps |
|---------|--------|--------|--------|---------|-----|
| Hsu (2013) [3] | 88.50  | 86.60  | 85.70  | 86.93   | 7.00|
| LSTMs (2016) [13] | 94.85  | 94.19  | 88.38  | 92.47   | None|
| DeepFCN (2016) [26] | 97.90  | 97.60  | 98.20  | 97.90   | 69.40|
| Zhuang (2018) [9] | 99.41  | 99.31  | 99.02  | 99.25   | 38.00|
| Proposed     | 99.13  | 99.20  | 99.21  | 99.18   | 78.41|

### Table IV: AOLP Error Study

| Image | Ground truth | Predicted | Cause of failure |
|-------|--------------|-----------|------------------|
| 0750J0 | 0750JC       | Character ‘0’ covered and incomplete. |
| 3L2556 | 3L25565      | Background treated as part of license plate. |
| Y88096 | Y88096       | Blurry image leads to prediction failure. |
| 2E5507 | 2E5507       | ‘E’ character is incomplete. |

### Table V: UFPR Results

|         | Accuracy (%) | fps |
|---------|--------------|-----|
| [5]    | 78.33 (47/60) | 35  |
| Sightound [5] | 70.00 (72/60) | None|
| OpenALPR [5] | 56.67 (34/60) | None|
| Proposed | 76.66 (46/60) | 43  |

### Table VI: UFPR Error Study

| Image | Ground truth | Predicted | Cause of failure |
|-------|--------------|-----------|------------------|
| AKT 8174 | 0G27        | Completely failed on multiple-row license plates. |
| ALJ 9348 | B7Q2        | Completely failed on multiple-row license plates. |
| IOZ3616 | BIZ3616     | ‘O’ character extremely similar to ‘O’. |
| AIQ1Q56 | ATQ1Q56     | ‘1’ character is shadowed. |

### A. AOLP Dataset

The application-oriented license plate benchmark dataset (AOLP) includes 2,049 Taiwan license plate images and is divided into access control (AC), law enforcement (LE), and road patrol (RP) scenarios. In this dataset, of the three subsets, the LE subset seems to be the most challenging and most similar to real-world scenarios. The LE subset contains 757 images of vehicles violating traffic laws that were captured from roadside cameras under various illumination and weather conditions; the image backgrounds are cluttered with road signs and sometimes single frames even contain multiple license plates. The AC and RP subsets, in contrast, are more or less rigid scenarios in that most vehicles are very close to the camera.

In this experiment, we compared the proposed method with four approaches: [3], [13], [26], and [9]. We followed the same training/test split as in [13] and [9]: two subsets for training and one for testing. The experimental results are shown in Table III. They show that not only does the recognition accuracy of the proposed method outperform three previous works [3], [13] and [26], but the recognition speed is also faster than these methods, even on less powerful hardware such as the GTX 1070. While the error rate of the proposed work is slightly higher than that of [9], our running speed is twice as fast, which suggests that there is still room for improvement. For example, we could sacrifice running time by using a heavier or more complicated model for more accurate predictions. In Table IV we analyze a few failure cases. Recognition failures are caused mainly by poor image quality, as mentioned in [9]. Moreover, the dataset contains images that are difficult even for human beings to recognize, such as the first sample in the table, in which the first and last characters are blocked by the surroundings.

### B. UFPR-ALPR Dataset

The UFPR dataset consists of 4.5k images: 1.8k for testing, 1.8k for training, and 900 for validation. In this dataset, images extracted from videos that are captured from static cameras are divided into different subsets, each of which contains 30 images with only one vehicle. Actually, every image is a single frame of the original video, so the background has no significant change compared to the AOLP dataset. We conducted experiments with the same settings as in [5] except that we used YOLOv3 for vehicle and license plate detection, unlike the previous experiment which requires only license plate recognition. This dataset is thus not as challenging as the AOLP dataset, and image quality is also far better than that of AOLP (images in the UFPR dataset are 1920 × 1080, whereas those in AOLP are around 320 × 480 or even lower), but to verify the robustness and the ability of environment adoptions, we still evaluate the method on various datasets.

In this experiment, we compared the proposed method with [5]. Because each subset contains images of the same vehicle, we could simply use the majority vote to produce the final prediction result of every subset as in [5]. The results are shown in Table V. At first glance, it appears that our method performs worse than [5]. After carefully inspection, we find that our prediction model does not correctly predict license plates with two rows. Of the 60 different vehicles in the testing set, 12 motorcycles are all equipped with two-row license plates. In our network design, as the CTC model treats the license plate as a collection of characters within a single row, the current proposed method does not fully recognize license...
plates that have multiple rows. Again, we demonstrate and analyze failed samples in Table VIII.

Due to time constraints, we were unable to modify the proposed method to account for multiple-row license plates. We instead conducted another experiment on the same dataset but without the motorcycles. We randomly chose 50 subsets that consisted only of images of non-motorcycle vehicles from the entire dataset, with the remaining images for training. The results are shown in Table VII: the results without multiple-row license plates indicate that the proposed method is still robust and sufficiently accurate under various environments in different countries, although it is currently limited to single-row license plates. Due to the segmentation-free recognition architecture and the latest YOLOv3 improvements, the proposed method clearly achieves a significantly higher fps than those in China and Japan.

C. NP-ALPR Dataset

The last experiment was conducted on the proposed NP-ALPR dataset. Because our model was already pre-trained on a similar private dataset, for this experiment we randomly selected 1500 images on which to evaluate the proposed method. As mentioned in the previous section, as diverse conditions such as weather conditions and times of day are covered in this dataset, this would be the most practical test in this paper. The proposed method correctly recognized 1479 license plates (98.60%) at more than 70 fps on a GTX 1070 GPU. Analysis of the failed samples is given in Table VIII.

In the experiment, we observe that most error cases were at night, during which rear lights tend to overexpose cameras, thus increasing the difficulty of license plate recognition. Another difficulty is the long range and tilted angles between the camera and vehicles; also, the captured images are often seriously blurred or distorted despite the large 1920 × 1080 images.

We note that these extremely distorted and blurred samples are difficult even for humans to fully recognize. Nevertheless, the proposed method still achieves over 98.60% recognition accuracy, which is outstanding in and of itself.

V. CONCLUSION

In this paper, we present a novel real-time network architecture combined with the latest works which not only facilitates highly efficient recognition for deployment in real-world applications but also yields improved overall accuracy. We evaluate the proposed method on three different datasets and compare the results with state-of-the-art approaches, showing that it achieves outstanding recognition accuracy and fast running times. Even though our method does not significantly outperform all previous works, it runs on cheaper hardware such as the GTX 1070 GPU, unlike most previous works which use the GTX 1080 Ti or higher-level hardware. As future work, we intend to introduce deblurring algorithms into our method to improve accuracy under environments such as that in Table VIII and plan to further optimize the affine transformation model to reduce the entire running time and errors caused by incorrect tilting correction. In addition, we plan to recognize multiple-row license plates to support scenarios such as that in UFPR-ALPR. Finally, we also intend to support recognition of license plates with non-ASCII characters such as those in China and Japan.

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