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Automatic Vehicle Detection and Identification using Visual Features

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By

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ABSTRACT

In recent decades, a vehicle has become the most popular transportation mechanism in the world. High accuracy and success rate are key factors in automatic vehicle detection and identification. As the most important label on vehicles, the license plate serves as a mean of public identification for them. However, it can be stolen and affixed to different vehicles by criminals to conceal their identities. Furthermore, in some cases, the plate numbers can be the same for two vehicles coming from different countries. In this thesis, we propose a new vehicle identification system that provides high degree of accuracy and success rates. The proposed system consists of four stages: license plate detection, license plate recognition, license plate province detection and vehicle shape detection. In the proposed system, the features are converted into local binary pattern (LBP) and histogram of oriented gradients (HOG) as training dataset. To reach high accuracy in real-time application, a novel method is used to update the system. Meanwhile, via the proposed system, we can store the vehicles features and information in the database. Additionally, with the database, the procedure can automatically detect any discrepancy between license plate and vehicles.

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CHAPTER 1

Introduction

In recent years, the transportation complexity has increased dramatically with the increase of the population in the world. Consequently, there is mountainous traffic work for different agencies due to the rise of vehicular movement. These organizations, for example, law enforcement agencies, who are responsible for monitoring each vehicle and arresting the illegal vehicles, need to do a lot of work such as checking if the license plate is registered. However, a huge number of vehicles in the street makes the work harder. Hence it is necessary to recognize the vehicles using machine learning techniques, and automatic vehicle identification has become an essential stage in the modern traffic system.

1.1 Automatic vehicle Identification system

Automatic vehicle identification and recognition system [41] is an autonomous technique applied in traffic system including electronic toll collection, border and customs checkpoints, etc. With hardware like camera, the system can recognize each unique vehicle correctly and quickly. As the most important part, automatic license plate recognition (ALPR)[12] is one form of the vehicle identification. It is an image process technology used to identify vehicles by reading the vehicle registration plates. It plays a significant role in a modern intelligent transport system. It can be used to enforce traffic bylaws, collect tolls on bridges and identify a person of interest to law enforcement. Figure 1 shows an example of ALPR application in Law enforcement With ALPR system, we can recognize each car with high accuracy and efficiency.

Figure 1: ALPR applied in Law enforcement [13]

1.2 Research Motivation

In 2016, there were over 33.7 million registered vehicles in Canada [4], compared with 2009 stats [28] which had nearly 20.5 million. This fact reflects that there was a dramatic increase during about seven years. This significant increase enforced modern transportation system to promote the performance of traffic controlling system. Therefore, in order to maintain the traffic effectively and safely, automation and artificial intelligence have become the mainstream in modern times. Numerous methods involving Machine learning have been invoked in the systems, which can monitor and control the transportation via identification and recognition. Additionally, the innovative technology will be applied in other systems, such as toll collection and parking lot access control. Application in these systems can satisfy great needs of our real life.

With the growing speed of registered vehicles, more and more ALPR algorithms have been proposed in recent years. However, the results, which are derived from these algorithms, are highly dependent on the camera or image quality. Additionally, complex lighting conditions and noise of the images make success rate and accuracy of these procedures unsatisfying. This means that the vehicle to be identified must be photographed many times until the set of hardware can recognize it successfully, which will cost much time and energy. Hence, it is extremely convenient to develop or modify one ALPR program that can work efficiently and accurately.

Unfortunately, in some cases, there are variant illumination, perspective distortion and interference characters due to the quality of the camera or the condition of the weather. As a result,the accuracy is very low, which can lead to huge cost of human labor. In addition, plates on the vehicle can be stolen and affixed on different cars. Therefore, license plate number cannot be the only information to detect and identify the vehicle. We need to identify one unique with more information such as the province of the plate and the type of the vehicle. Hence, we have developed a system to identify and recognize the vehicle efficiently and with high accuracy.

1.3 Problem Restatement

With the development of the nowadays technology and the rise of the number of vehicles all over the world, the intelligent traffic system more highly depend on the automatic vehicle recognition system. Hence the vehicle detection and recognition system must have a good performance in both accuracy and time complexity. There are some tips we need to focus on.

1. For development in real-time application, in each phase of the system, the testing image should be modified for next procedure.

2. Feature extracting and selection are important. Model of the program should be rebuilt to obtain more useful features, with which the procedure can detect and recognize the license plate accurately.

3. For security and accuracy, more features obtained from the vehicle should be used in the system.

1.4 ALPR system

Generally, ALPR system consist a series of methods [16], which are associated with some important techniques. These approaches come from some areas such as machine learning, pattern recognition and computer vision. Hence, algorithm selection and modification become the crucial parts of the procedure. Based on that, what we do is to design a excellent system to reach the ultimate purpose of the system, which is to get the license plate number from the images captured by the camera.

Basically, the system consists of six steps. The Figure 2 shows the steps of ALPR system.

1. Image capture

   - It is a hardware based process, which is affected by the quality and type of camera, lighting strength, illumination and weather conditions. As a result, an image file is collected.

2. Plate detection and localization [19].

   - This stage is responsible for finding and isolating the plate on the image, which involves the search, segmentation and transformation of the plate in the file obtained from the previous stage.

3. Image binarization and normalization.

   - Binarization is the process of converting a pixel image to a binary image [38]. The threshold value of the image can be derived in different binarization methods. This includes global thresholding [34], adaptive method [30], Niblack's Algorithm [27], etc. These methods can separate the foreground from the background. Consequently, this technique can give us the foreground text in white and background in black.

   - Normalization consists of serval detection methods for noise reduction, image smoothing and image orientation.

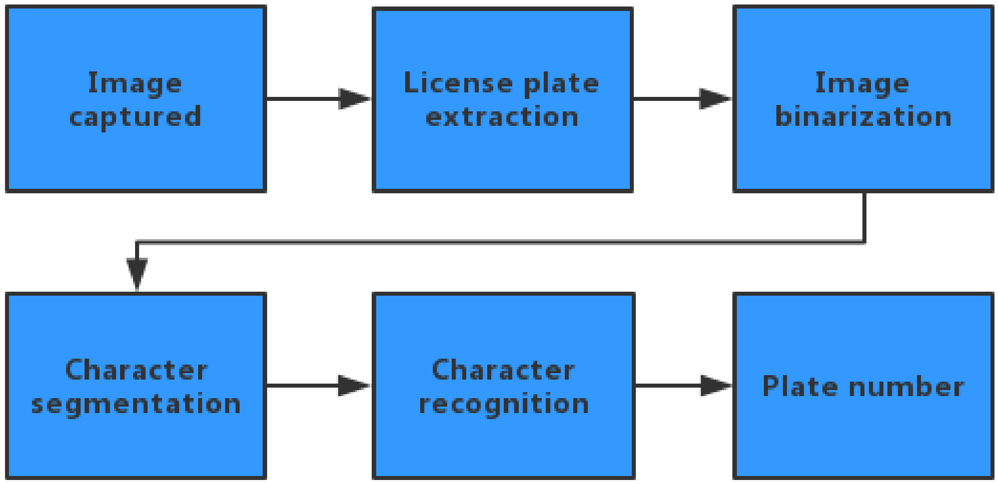


Figure 2: A simple flowchart of ALPR

4. Character segmentation.

    - Character segmentation is a critical area of character processing and an important preprocess for character recognition. With previous steps, plate has been extracted. To identify each character, individual characters must be detected in the image. Several approaches have been proposed such as projection, connected components or morphology. As a result, each character is extracted.

5. Character recognition.

    - Optical character recognition(OCR) is the main stage in ALPR [42]. Input characters may be noisy or broken. OCR techniques must be able to tolerate these cases, and derive a result with a high accuracy.

1.5 License plate province detection

In some cases, plates on the vehicle can be stolen and affixed on different cars. Therefore, license plate number cannot be the only information to detect and identify the

Figure 3: License plate samples from different provinces in Canada [43]

vehicle. We need to identify one unique vehicle with more information such as the province of the plate and the type of the vehicle.

Figure 3 shows some sample license plates from different provinces in Canada. From that we can see the province characters in Canadian license plate are mostly on the top of the numbers, and are smaller than the numbers. Consequently, it is extremely hard to recognize them using OCR. Therefore, the best way to detect the province is using feature matching. It takes the descriptor of one feature in the first set and is matched with all other features in the second set using Euclidean distance [10].

1.6 Vehicle shape detection and recognition

The goal of this stage is to detect the type of the vehicle. It can be seen as a task for image classification. In this procedure, each input image is classified with its features.

The features determine the type of the image. Therefore, in classification, if we desire to get true type of the vehicle in the image, the type of classifier and features should be detected. In the proposed system, there are some types which can be classified, namely:

1. Sedan and sports car: Sedan is a passenger car with an enclosed automobile body having two or four doors and seating four or more persons on two full-width seats.

2. Hatchback: Hatchback car is a kind of car, in the ending of which there is a single door that is lifted to open. And the car body is usually for cargo storage.

3. Sport utility vehicle(SUV): SUV is a vehicle classified as a light truck, which is similar to a station wagon.

4. Pickup: Pickup truck is a light truck having an enclosed cab and an open body with low sides and tailgate.

5. Cube van: "Cube van is a van with a cube-shaped storage compartment that is wider and taller than the front of the vehicle" [11].

Figure 4: Classification of vehicles [23]

1.7 Thesis Contributions

In our proposed system, we has developed a novel method for detecting the license plate. Many useful features are extracted from the images which serve as the classification vectors. For high performance in classification, an adaptive classification is employed to detect the license plate. For deriving result with high accuracy in character recognition, there are many image preprocessing programs in our system such as image orientation, image binarization, character segmentation, etc. Our license plate recognition model has a good performance both in success rate and time complexity. We have also developed a method to detect province from the license plate. To make the security of the system high, we use a neural network model to recognize the shape of the vehicles. The license plate recognition, province detection and vehicle shape recognition make our system reliable for application in an intelligent transportation system.

CHAPTER 2

Literature Review

This chapter provides a brief reviews of the previous research on license plate detection and recognition using machine learning and computing vision methods.

2.1 Edge-based method for license plate detection

An edge based multi-stage approach of license plate localization was proposed by Satadal Saha et al [37]. In this paper, license plate image is extracted from original image by edge detection. Localization of plate is undoubtedly a challenging task since there are significant variations in plate size, color, lighting condition and spatial orientations of license plate in images. In this work, at preprocessing stage, three steps are employed.

1. Gray scale conversion
    - By the following formula, the 24-bit color image can be converted into 8-bit gray image.

$$Gray = 0.59 \times R + 0.30 \times G + 0.11 \times B \tag{1}$$

2. Median filtering
    - As one of non-linear filter, it can calculate the median of the gray values of a pixels neighbors. In this stage, they use 3×3 masks to get eight surrounding neighbors gray value and replace the pixel value with the median value. As a result, the function could remove salt-and-peeper noise from the image.

3. Contrast enhancement

   - Histogram equalization technique is invoked to enhance contrast of the images. In the procedure of the conversion, the total number of pixels in the image is N and the number of pixels with the gray level k is n_k. Then the stretched gray level S_k is calculated by he following formula.

$$S_k = \sum_{j=0}^{k} \frac{n_j}{N} \times 255 \tag{2}$$

After that, edge detection is implemented with Sobel edge operator. Via prominent vertical edges, they develop several stages to localize the plate.

1. Minimum and maximum threshold value is derived from the dataset. Then the image is scanned to get mean value and variance value of each edge pixel positions. Compared with the threshold values, potential band of rows is identified.

2. For each band, diagonal corners are detected by calculating the minimum and maximum values of the edge gradient value. With these two points, the maximum area of the license plate are indicated.

3. The minimum value of height H_min is dependent on the height of the characters in the character set. It is obtained by getting the average value of the vertical edges in the bounding box which derived from the second stage. Among theses new bounding boxes, the overlapped or very closed boxes were merged.

4. From the generated dataset, the procedure obtained the average value of aspect ration and the area, by which noise boxes are removed.

In this experiment, 500 images with the resolution 704×576 pixels are selected as training dataset. Meanwhile, another 500 images are used for the test. In the result, the false negative was only 8%, which meant that there were 40 samples in which true license plates were not found or false location were detected as license plate. If the false negative cases were just considered as wrong cases, the accuracy of this license detection technique could reach to 89%. This proposed program shows a good performance in different lighting conditions, shadows and complicated scenes. However, the main limitation of the system is that it will not be good if the image are more noisy.

2.2 ALPR based on fuzzy maps

Shyang-Lih Chang et al. [7] proposed a license plate image technique consisting of two main models: a license plate locating model and a license number identification module. Specifically, the license plate candidates extracted from the first model are examined in the identification model to reduce the error rate. In the first model, several features such as color are taken into consideration to determine the license plate region. Initially, they use color edge detection to compute edge map E which contains three types edge (i.e., black-white, red-white and green-white edges) due to the fact that there are just four kinds of color(white, black, red and green) for the plate and character in Taiwan. To detect the color edges, these three kinds of edges are taken into consideration. The RGB color differences ($\triangle r, \triangle g, \triangle b$) can be calculated to find the edge. Next, with unique formulas, the program can transform RGB space into HSI space that denote (red, green, blue) and (hue, saturation, intensity) values of an image pixel, respectively. The transform formula is as below.

$$\begin{aligned} I &= \frac{(r+g+b)}{3} \\ S &= 1 - \frac{min\{r,g,b\}}{I} \\ H &= \cos^{-1}\left\{\frac{(r-g)+(r-b)}{2[(r-g)^2+(r-b)(g-b)]^{\frac{1}{2}}}\right\} \end{aligned} \tag{3}$$

Besides, from given four maps E, H, S and I the stage can derive four fuzzy maps $\hat{E}$, $\hat{H}$, $\hat{S}$ and $\hat{I}$ based on the idea that the entry of any cell in the map expresses the degree of the cell possessing the property due to the fact that each map can encode some features about the scene. Moreover, two fuzzy aggregators will be employed to integrate the map. As a result, the license plate candidates are then extracted.

The identification module consists of two main stages, preprocessing and recognition. The preprocessing stage contains three tasks, namely, binarization, connected component labelling and noise removal. After these processes, segmentation and recognition will be invoked sequentially. In the segmentation procedure, three functions (delete, merge and split) is applied to the surviving components until no character can be extracted. The character recognition is composed of three steps which are character categorization, topological sorting and self-organizing recognition. First step is that input character is distinguished as numerical or alphabetical by compositional semantics of license numbers. Next, topological features of characters is calculated and compared with stored templates. Finally, a test will be formed, where the template that best matches the input character is detected. This proposed work is much less restrictive compared to most of the other work that restricted their working conditions and still has a high success rate. However, the identification model takes about two seconds to recognize the numbers, which means it take much time and the complex program need to be modified.

2.3 Character recognition with visual features

Salah Al-Shami et al. [1] proposed a new feature extraction method for license plate number recognition which focus on the character recognition. Some approaches to recognize characters is usually taking lines as features. Here, the algorithm they developed searches for the line containing a feature or a group of combined features. Each line of character is selected manually by the process. These features are extracted from horizontal lines and vertical lines. In the horizontal lines feature extraction, three types of features are employed, which are presented as following lists.

- Feature 1: the number of transitions is counted in each horizontal line by the program.
- Feature 2: the percentage of white pixels is calculated in each horizontal line from the binarization image

- Feature 3: the image is divided into 3 identical regions vertically, which are left, middle and right. The feature is 0 or 1 in each region, which depends on the occurrence of transitions in each region.

Next, these three features are modified into five features.

- Feature 1: Transition features are stored in the database as an integer number.
- Feature 2: the percentage-of-white features are float number. And quantization process is applied. The formula is showed below, in which the value Q could range between 2 and 100.

$$Percentage\_of\_White(Q) = \lceil (Percentage\_of\_White * Q) \rceil \tag{4}$$

- Feature 3: Position-of-transition features are stored as a code of three binary bits. For example, if the original feature is "left=1, middle=0, right=", it will be stored as "100".
- Feature 4: This feature will be derived by combining Feature 1 and 2 in a decimal format. For example, the value of Feature 4 may be 16.3, which means that the value of Feature 2 is 16 and the value of Feature 1 is 3.
- Feature 5: It is grouped by combining the first 3 features together in a decimal format. If the value of Feature 5 is 8.3111, it means that the Feature 2 is 8, and the Feature 1 is 3 and the Feature 3 is coded as "111".

Then, classification model will be invoked after feature selection, in which a cube constructed from the lines is composed of horizontal lines and vertical lines. Additionally, there are three dimensions.

- Dimension 1: 5 features discussed above
- Dimension 2: The set of horizontal lines
- Dimension 3: The set of 10 classes from 0 to 9.

In the third dimension, the set of 10 classes is used for labelling the character. After construction, feature selection is employed in the program, which can search for dissimilarity of features. From the modified model, the recognition tree can be built to recognize the numbers on the plate. The tests are performed on the real KSA (Kingdom Of Saudi Arabia) license plate. Consequently, experimental results implemented using MATLAB, showed the efficient and productive way of the system with an over 95% accuracy.

2.4 Character recognition based on Template Matching

A modified template matching Correlation algorithm has been proposed by Ali Farhat et al. in [14]. Numeric ALPR systems in the past, have faced different kinds of challenges for character recognition. Some of the methods used extensive calculations which could slow down the operation. Hence, they have developed four algorithms to overcome the limitations: Vector crossing, zoning and combined zoning-vector and template matching correlation. First three algorithms are based on feature extraction techniques and the last one is application of correlation technique.

To distinguish numbers, three vectors are used in vector crossing process. The three vectors are vertical vector, horizontal vector at one-third of image and horizontal vector at two-third of the image. Then with counting numbers of the vectors, the ten characters($0-9$) are distinguished except the characters "2", "3" and "5" since they have the same number of the vectors. Table 1 presents the result of this approach.

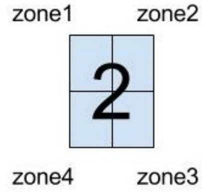


Figure 5: The zones of each image

Due to the same number of vectors for "2", "3" and "5", the second method

Table 1: Vector crossing using three vectors

Vector Crossing	Digits Crossing									
	0	1	2	3	4	5	6	7	8	9
Vertical Vector	2	1	3	3	3	2	3	2	2	3
Horizontal Vector1	2	2	1	1	1	1	1	1	2	2
Horizontal Vector2	2	1	1	1	2	1	2	1	2	1

Zoning has been employed. Here, each character image will be divided into four zones as the Figure 5. Densities of the image in each zone are derived by the algorithm to determine the characters. The third approach is the combination of the previous two methods. In that, density of the image is calculated. Meanwhile, the method will take one or two vector crossing into account to reduce the error rate and increase the probability of correct character recognition. However, the three algorithms cannot determine a noise in the image. Hence, they develop a system based on template matching. In this system, correlations of two images is evaluated by the following expression.

$$r = \frac{\sum_m \sum_n (A_{nm} - \bar{A}) \cdot (B_{nm} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{nm} - \bar{A})^2) \cdot (\sum_m \sum_n (B_{nm} - \bar{B})^2)}} \tag{5}$$

After that, threshold value is set to be 0.45 to detect the noise. Additionally, the value or r will tend to 1 if the images match.

This system, which implemented and tested with 2790 characters, has the extremely recognition rate at 99.5% and takes 1.95 ms to precess an image. However, the limitations of the approach is that it just can recognize 10 numbers instead of the alphabet. If more templates are added to the system, the success rate may decline since some characters share the same density and vector.

2.5 Character recognition based on Neural Network

Christos-Nikolaos Anagnostopoulos et al. [2] proposed a new algorithm for license plate identification. For faster detection of regions of license plate, they developed a novel method called sliding concentric windows(SCW), which can describe the irregularity in the image based on image statistics. The SCW segmentation algorithm involes following steps.

1. Two concentric windows A and B were created for the upper left corner pixel of the image.

2. Mean value were obtained from both of the windows.

In the program, the RoI(Region of Interest) will be detected if the ratio of the statistical measurements in the couple of windows reaches a threshold. The formula is as below.

$$RoI = \begin{cases} 0 & \text{if } \frac{M_B}{M_A} \leq T \\ 1 & \text{if } \frac{M_B}{M_A} > T \end{cases} \tag{6}$$

where M is the mean value of the two windows and T was set manually. Next, image masking, binarization with Sauvola[38] and connected components analysis (CCA) are employed in sequence. In the image masking phase, the output of the SCW method are viewed as the mask, which is used in the AND masking operation. After that, Sauvola method is invoked to binarize the image. The threshold value is derived by the following equation.

$$T(x,y) = m(x,y) + [1 + 0.5 * (\frac{\sigma(x,y)}{128} - 1)] \tag{7}$$

where $m(i,j)$ and $\sigma(i,j)$ are the sample mean and variance, respectively. In next stage, CCA is applied in the binarization to scan the image and label its pixels into components based on pixel connectivity. As a result, license plate region is detected successfully.

In license plate processing stage, they create an approach to segment characters, in which bounding box of characters are determined using column and row standard deviation criterion. Then, probabilistic neural network(PNN) is invoked to recognize the characters. The process takes individual character image(9X12) pixels value as the input feature vector, which means the input layer consists of 108 nodes. Besides, the pattern layer takes 5 image patterns of every character as nodes to organize the training set. As a result, possible character is determined in the output layer. The proposed system relies highly on the lighting condition and the physical appearance of the plates. In some cases, the program cannot detect the plate due to the illumination condition or the quality of the plates.

2.6 Optical character recognition for handwritten English

Vijay Patil and Sanjay Shimpi [32] proposed a Character Recognition System for handwritten English. "It is extremely difficult to recognize the handwritten characters since there is a great variation of writing style, different font size and orientation angle of the characters" [32]. In their sytem, each character is represented by a character matrix with the size 8×5. If the size of the character matrix is too small, the letters may not be presented properly. If the size of the matrix is too big, the train process will take more time. Hence, size 8×5 is good for the system. In the matrix, black stands the vector of 1 and white stands for 0. The Figure 6 shows three matrices for character "A", "B" and "C". In the architecture of the neural network, there are $40(= 5 \times 8)$ inputs, 26 neurons in its output layer and 5 neurons in hidden layer. The log-sigmoid transfer function is used in tow-layer network. The weights of the neural network is updated by calculating the error between actual output and the target output. In training process, the network on ideal samples and noisy samples. The procedure is illustrated below:

First Character 'A'	Second Character 'B'	Third Character 'C'
0 0 1 0 0	1 1 1 1 0	0 1 1 1 1
0 1 0 1 0	1 0 0 0 1	1 0 0 0 0
1 0 0 0 1	1 0 0 0 1	1 0 0 0 0
1 0 0 0 1	1 1 1 1 0	1 0 0 0 0
1 1 1 1 1	1 0 0 0 1	1 0 0 0 0
1 0 0 0 1	1 0 0 0 1	1 0 0 0 0
1 0 0 0 1	1 0 0 0 1	1 0 0 0 0
1 0 0 0 1	1 1 1 1 0	0 1 1 1 1

Figure 6: Character matrices for character "A", "B" and "C"

1. The dataset is split into two sets: a training set and a test set. The target output is normalized to the range $(0, 1)$.

2. All weights and biases are initialized to random values from -1 to $+1$.

3. Each neuron sums the weighted input. The forward propagation of first input pattern passes weighted input through the nonlinearity and the sum is sent to next layer.

4. Difference between the actual output and target result is derived.

5. The difference update each weight by using Back propagation rule.

6. Forward propagation is invoked in the next input pattern.

7. Step 3-7 is repeated until the error falls below a threshold value.

There are some learning factors that can affect the performance of the neural network, such as the number of hidden neurons and the number of hidden layers. "The dimension n of the input vector and the number of separable regions in n dimensional Euclidean input space can detect the number of hidden neurons" [32].

In the test, there are 5 neurons in hidden layers and 22 hidden layer neurons. The experiment gets an accuracy of more than 70%. In the handwritten recognition problem, the result is not so bad. However, the accuracy is extremely important to the license plate recognition system. And the features they used are very simple.

Though the training of the system is fast, the features sometimes may provide wrong information for training system.

2.7 Vehicle detection and classification based on HOG

A vehicle shape classification model has been presented by Zezhi Chen and Tim Ellis [8]. Vehicle classification is a crucial stage in Intelligent Transportation System (ITS). Most of the classification task is done by human, which has a bad performance in time complexity. However, an automatic system can provide a more accurate and lower cost solution. Classification model contains two parts: feature extraction and classifier selection. In their approach, measurement-based features (MBP) and the histogram of orientation gradients (HOG) features are used to classify the road vehicles into four categories: car, van, bus, and motorcycle. In MBP features, there are serval different measurements shown below to make up the feature vector including perimeter, width and height of the bounding box, convex area and so on.

In camera calibration process, to compute the transformation between 2D image points and 3D world points, four systems need to be determined: world, camera, camera sensor plane and image plate. For implementations of camera calibration, they used Google Earth as the tool to provide a plane view. As a result, the car wireframe model is projected into the image. This model is used in model-based classification. In this method, “the vehicle silhouettes are matched against 2D projections of the 3D models” [8]. The best 3D model can be found to match the original vehicle model.

For classification, two classifiers are used, which are Random Forest (RF) and Support Vector Machines (SVM). Due to the multiple classification problems, they decided to use one-vs-all strategy. In the phase, one of the four classes is considered as one group and the others are seen as another group. Then, after finding the hyperplane between two groups, the classifier RF or SVM is repeated for the group which has more than 1 class until each object is classified. From the results, they concluded that SVM is better than RF in the system. The true positive rate reaches to 0.9911. The model they have presented is a novel vehicle type classification, which provides an accurate and reliable performance. However, the models among the four vehicle types are very different. Sometimes 3D models of two vehicles such as hatchback and SUV, may be similar. In this case, this system may be hard to detect the type.

CHAPTER 3

Material and Methodology

3.1 Overview of our approach

In this chapter, we will propose three systems for vehicle detection and recognition, which are automatic license plate recognition, province detection and vehicle shape detection and recognition respectively. Figure 7 shows the flowchart of the proposed system. In the system, ALPR and vehicle shape classification are individual. Therefore, they can be executed at the same time. Additionally, after plate detection, plate recognition and province detection can also run at the same time. This design can reduce much time for application in real-time system.

The recognition program is based on the Canadian vehicles. Hence, the data set that we tests are from the Canada. The approach we developed consists of four main stages:

1. License plate detection and localization
2. Processing with licence plate image
3. Character segmentation
4. Character recognition

These four stages are sequential. The result derived from an earlier stage provides an input to the next stage.

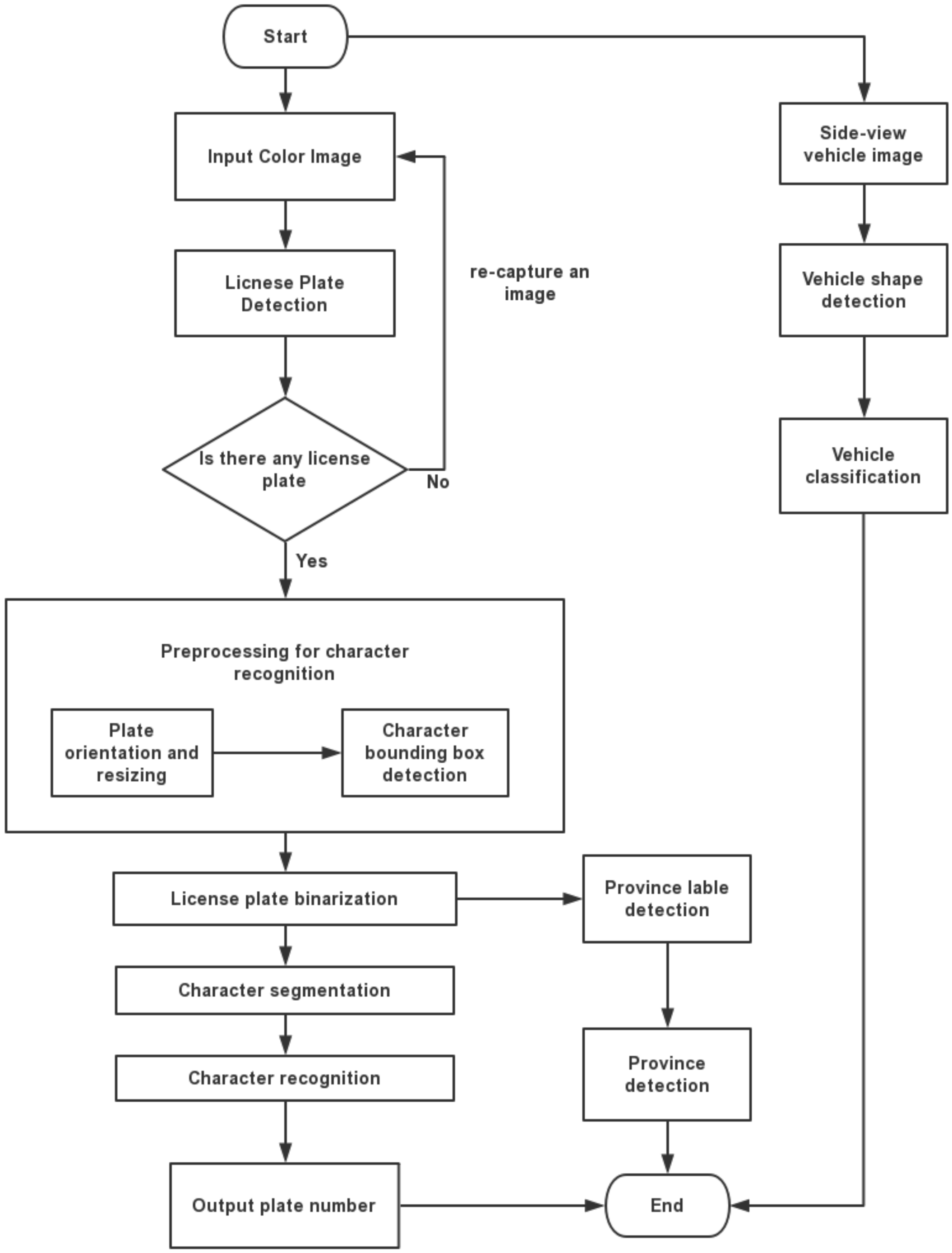


Figure 7: Flowchart of the proposed model

3.2 Automatic license plate recognition (ALPR)

3.2.1 License plate detection and localization

License plate localization is a crucial stage in the system. The result derived from the stage will affect directly the performance of the recognition system. From literature review, we know that some approaches for localization are more productive, such as edge-based detection and fuzzy detection. However, these methods are restricted by lighting conditions, which motivate us to develop a system that can overcome these restrictions. To detect the license plate efficiently, we take feature description as our target, which means that if we learn about the features that can describe the number plates, we can extract them. Meanwhile, local binary pattern (LBP) [18] and histogram of oriented gradients (HOG) [9] are texture visual descriptors used for classification, of which the important properties are the tolerance against the illumination changes.

The basic idea of this phase is based on multi-stage structure, which is a kind of cascade classifiers. Figure 8 shows an overview of Plate detection procedure. The architecture is improved from [45] [26]. Instead of applying all features on one window, the program groups the LBP and HOG features into different stages. In the sequential stages, positive results from the previous stage will trigger the next stage classifiers, which uses the LBP and HOG features. The negative results are rejected immediately. Using this approach, we can detect the license plate image rapidly and accurately.

Histogram of oriented gradients(HOG)

The histogram of oriented gradients (HOG) is a feature descriptor employed in object detection program. It provides excellent performance in human detection [9]. The HOG feature descriptor is invariant to geometric and photometric transformations because it operates on cells in the image. And magnitude of gradients is large around edges and corners, which can pack in much information about object shape. The following list shows the procedure of HOG calculating. Figure 9 presents one HOG image.

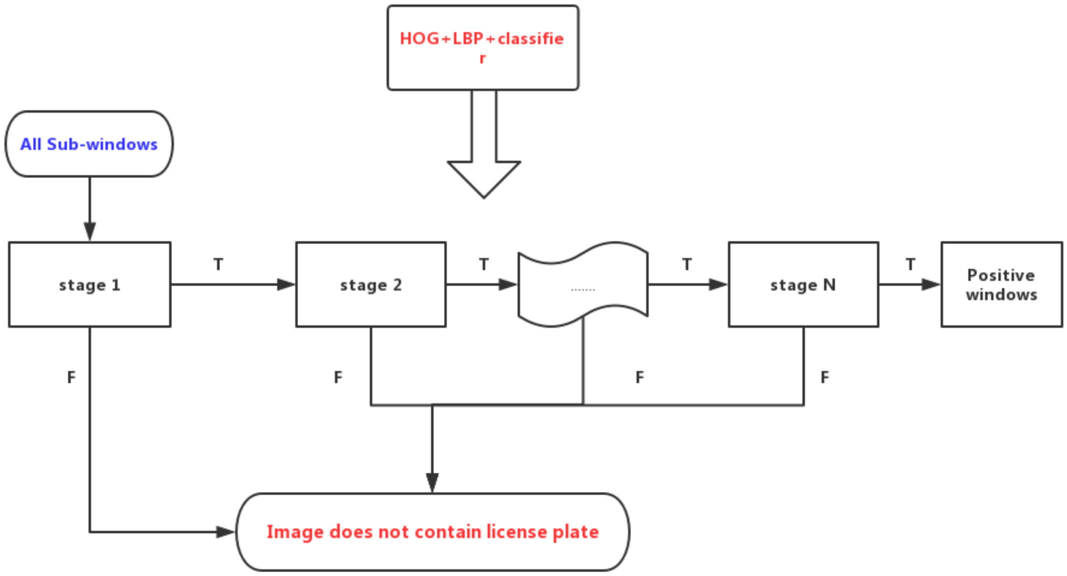


Figure 8: Overview of the License plate detection

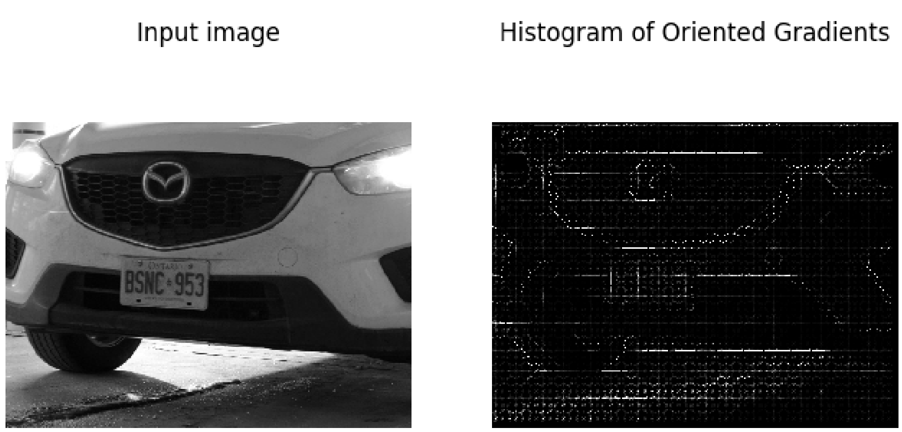


Figure 9: Converting the image into HOG image

1. Global image normalisation

   - To reduce the effects of local shadowing and illumination variations, gamma compression (correction) [17] is used. It can be described with a simple point-wise correction of the form [15]:

$$g(u) = u^{\frac{1}{\gamma}}, \tag{1}$$

where $u \in [0, 1]$ denotes the image pixel intensity. In our system, γ is set to 1.5, which can make the output image lighter than the original. When γ is set to be smaller than 1.5, images from our dataset are a little darker. When it set to be more than 1.5, the output image too light. Figure 10 shows the result of gamma compression.

Figure 10: Example of gamma compression

2. Calculating the gradient image in x and y.

   - Horizontal and vertical gradients can be calculated by Sobel operator [20], the operator is as below formula. Then, magnitude and angle can be calculated.

$$g = \sqrt{{g_x}^2 + {g_y}^2} \tag{2}$$

$$\theta = \arctan \frac{g_y}{g_x} \tag{3}$$

3. Orientation binning

   - The cell histograms is created in this step. Each pixel within the cell casts a weighted vote for an orientation-based histogram channel based on the values found in the gradient computation. The cells themselves can either be rectangular or radial in shape, and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees, depending on whether the gradient is unsigned or signed [9].

4. Block normalization

   - The normalization factor can be derived by the $L2 - nrom$ as following formula:

$$f = \frac{v}{\sqrt{\|v\|_2{}^2 + e^2}} \tag{4}$$

5. Calculating the HOG feature vector

Local binary pattern(LBP)

LBP computes a local representation of texture. This local representation is constructed by comparing each pixel with its surrounding neighborhood. Initially, the input RGB colorful image will be converted into grayscaling one by the following formula [29]

$$Gray = 0.299 \times R + 0.587 \times G + 0.114 \times B \tag{5}$$

where R, G and B are the image color channels' value, which red, green and blue respectively.

Next, each pixel of the image is labelled by LBP operator via thresholding 3×3 neighborhood of each pixel with the center pixel value. As a result, binary number is extracted as a LBP code. For each pixel in the grayscaling image, we select a neighborhood of size r surrounding the center pixel. A LBP value is then calculated for this center pixel and stored in the output 2D array with the same width and height as the input image. Then, we can calculate the LBP value for the center pixel. We can start from any neighboring pixel and work our way clockwise or counter-clockwise, but the ordering must be kept consistent for all pixels in the image and for all images in the dataset. Consequently, this process of thresholding, accumulating binary strings, and storing the output decimal value in the LBP array is then repeated for each pixel in the input image. The last step is to compute a histogram over the output LBP array. Since a 3×3 neighborhood has $256(= 2^8)$ possible patterns, our LBP 2D array thus has a minimum value of 0 and a maximum value of 255, allowing us to construct a 256-bin histogram of LBP codes as our final feature vector.

$$\begin{bmatrix} 193 & 151 & 172 \\ 095 & 150 & 142 \\ 117 & 120 & 143 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 1 & 1 \\ 0 & P & 0 \\ 0 & 0 & 0 \end{bmatrix} \rightarrow (11000001)_2 \tag{6}$$

Figure 11 shows example results with black (or white) representing pixels that are less (or more) intense than the central pixel. When surrounding pixels are all black or all white, then that image region is spot or flat.

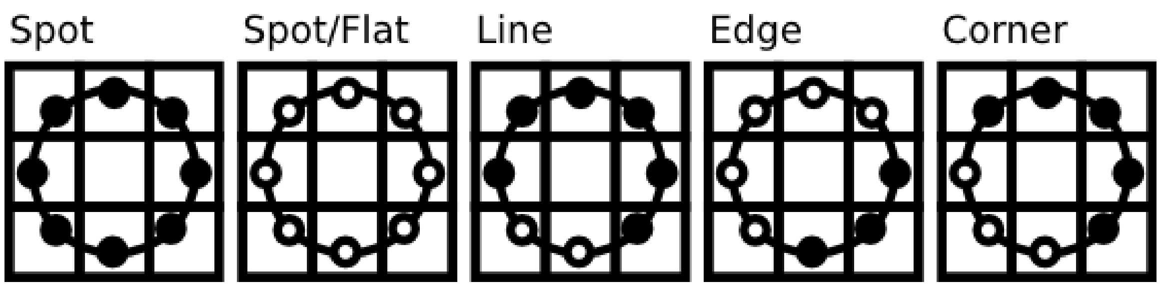


Figure 11: Example results of LBP [40]

Learning classification

Given a training dataset of positive and negative images, serval machine learning methods can be used as a classification function. In our proposed approach, Gentle AdaBoost is invoked to select the features and to train the classifier. Generally, AdaBoost is a form of learning algorithm which is used to promote the classification performance of a weak learning algorithm. It can provide strong guarantees in the procedure. It is proved in [24] that the training error of the strong classifier can almost reach to 0. The following figure is the steps of the AdaBoost [24].

In addition, the weak learning function is employed to select the license plate features or LBP histogram bin which can separate the positive and negative samples

Algorithm 1 Gentle AdaBoost

1. Given N examples, $(x_1, y_1), \ldots, (x_N, y_N)$ with $y_i \in [-1, 1]$
2. Start with $w_i = \frac{1}{N}, i = 1, 2, \ldots, N$
3. Repeat for $m = 1, \ldots, M$
   (a) Fit the regression function $f_m(x)$ by weighted least-squares of y_i to x_i with weight
   (b) Set $w_i \leftarrow w_i \cdot exp(-y_i \cdot f_m(x_i)), i = 1, \ldots, N$, and renormalize weights so that $\sum_i w_i = 1$
4. Output the classifier $sign[\sum_{m=1}^{M} f_m(x)]$

the best. Specifically, for each feature, the weak algorithm can detect the threshold function, which can make the number of misclassified examples minimum. The weak classification function $f_j(x)$ is composed of a feature f_j denoting the LBP histogram bin, a threshold value $_j$ and a parity p_j indicating the direction of the inequality sign. The formula is as the following.

$$f_i(x) = \begin{cases} 1 & \text{if } p_i f_i(x) \leq p_i \theta \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Cascade classifiers

For detection of the license plate in the sub-image, a cascade of classifiers is used, which can boost the detection performance while reducing the time complexity of the procedure. A cascade of classifiers is constructed like a degenerated tree, in which at each step, a classifier is trained to detect the license plate and to reject the majority of sub-windows where there is no any license plate. Specifically, Gentle AdaBoost is used as training classifiers in stages of the cascade and threshold value is adjusted to minimize false negatives. In the construction of the cascade classifiers, the previous strong classifier can derive a positive result. Then, the result can rigger the next classifier which is adjusted to get a higher detection rate than the last one. Conversely, a negative sample is instantly rejected at any stage of the procedure as shown in Figure 12.

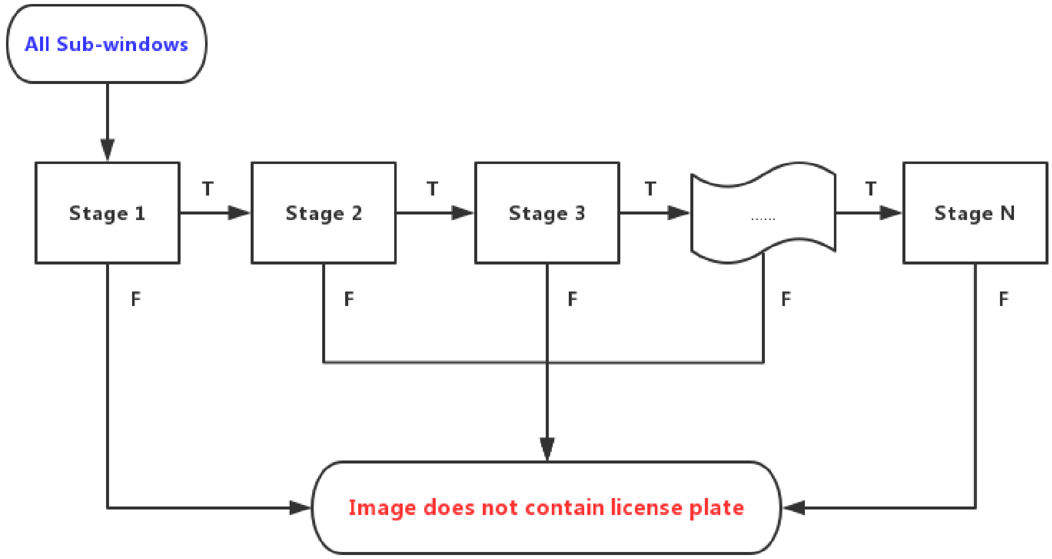


Figure 12: Flowchart of cascade model [44]

Generally, a lower threshold value results in higher detection rates and higher false positive rates [24]. Therefore, the threshold value can be adjusted to detect the license plate with high accuracy.

The proposed system has a good performance in detecting license plates on images with various types of illumination. Figure 13 and Figure 14 illustrate two examples of detection on the images with illumination. In the first case, there is a cover on the license plate. However, its LBP and HOG features still can be extracted and detected. In the second case, the noise does not affect the detection result. Both of them are detected successfully.

3.2.2 Processing with license plate recognition

The preprocessing stage consists of three stages, which are plate orientation, image binarization and character bounding box detection respectively.

Figure 13: Detection on an image with the covered plate

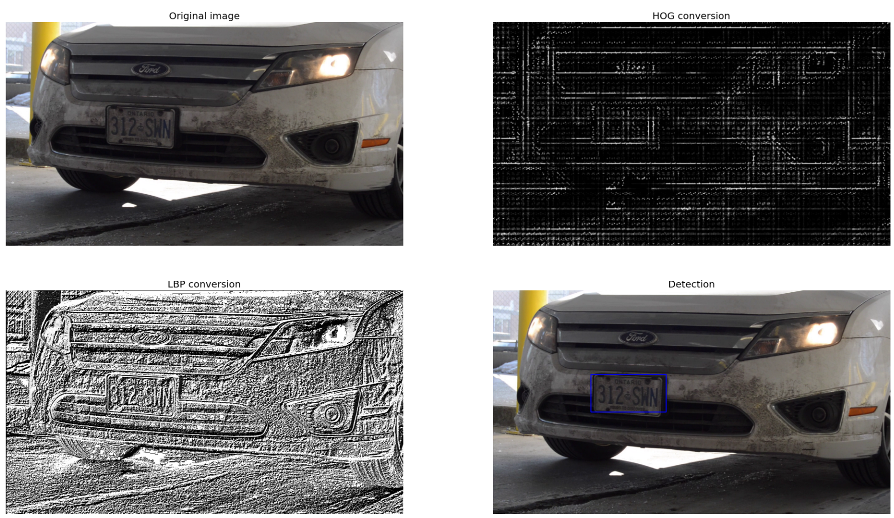


Figure 14: Detection on an image with noise

Plate orientation

In most cases, the camera capturing the vehicle image is not just directly in front of the vehicle, which means that there will be an angle with degree between the camera and the vehicle. Figure 15 shows the positions of camera and vehicle when the vehicle is in the test area. And Figure 16 is the real image which is captured by the camera.

From the image, we can see that the camera is in front of the vehicle at the right hand side.

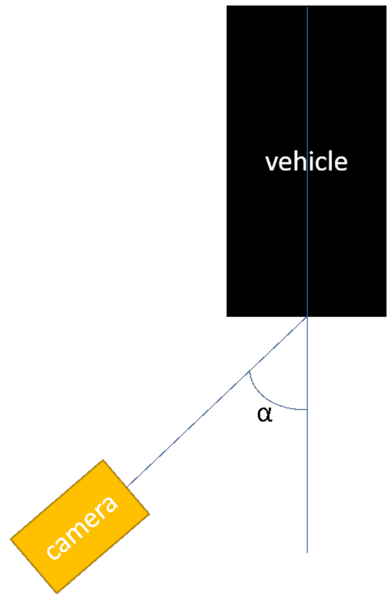


Figure 15: There is an angle between camera and vehicle

Figure 16: Vehicle image captured by the camera

From the related work, the edge-based detection gives us an idea to process with the plate image. With the image extracted from the previous step, we can detect the lines of the plate via Canny edge detection, which is a multi-stage algorithm to detect the edge of objects. The algorithm below shows the edge detection steps.

Algorithm 2 Canny edge detection

1. Use the Gaussian filter G(m,n) to smooth out the image $f(m, n)$.

$$g(m, n) = G(m, n) * f(m, n) \tag{8}$$

where $G(m, n) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{m^2+n^2}{2\sigma^2}\right)$

2. Compute gradient of $g(m, n)$ using any of gradient operators to reach

$$M(m, n) = \sqrt{{g_m}^2(m, n) + {g_n}^2(m, n)} \tag{9}$$

$$\theta(m, n) = \tan^{-1}[g_n(m, n)/g_m(m, n)] \tag{10}$$

The gradient operator can be Soble operator.

$$g_m(m, n) = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * f(m, n) \tag{11}$$

$$g_n(m, n) = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * f(m, n) \tag{12}$$

3. Threshold M is given as:

$$M_T(m, n) = \begin{cases} M(m, n) & \text{if } M(m, n) > T \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

After computing the threshold value M, we can derive the four edges of the license plate. Whereas, four corners of the plate are extracted from the four edges. It does not matter whether the region we extracted is rectangle. Because the four corners can be taken as four corresponding points. At the same time, the four target points are the four corners of one rectangle shape. We can calculate a perspective transform from these four points. This transform operator can convert the image into the ideal one for recognition. The transformation is:

$$\tilde{p}' = H\tilde{p}, \tag{14}$$

where H is a 3×3 transformation matrix, $\tilde{p}$ is the coordinate of the corresponding quadrangle vertices in the destination image, $\tilde{p}$ is the coordinate of quadrangle vertices in the source image. To obtain an inhomogeneous result p, coordinates are normalized by the following formula.

$$p_x = \frac{h_{00}x + h_{01}y + h_{02}}{h_{20}x + h_{21}y + h_{22}}, p_y = \frac{h_{10}x + h_{11}y + h_{12}}{h_{20}x + h_{21}y + h_{22}} \tag{15}$$

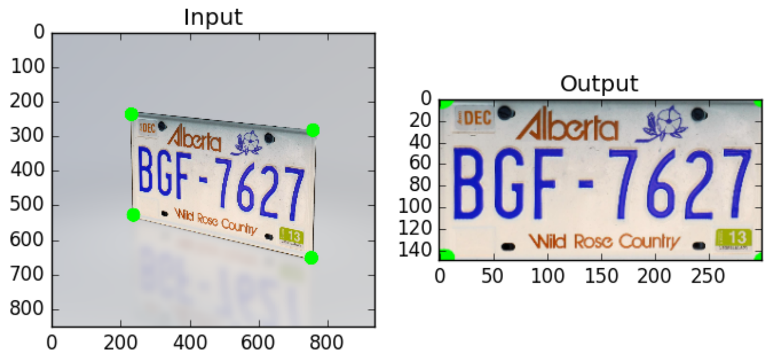
With this formula, we can project the source image into a destination image in a two-dimensional space. For testing the limitation of the program, we tested the image with the degree ranging from 30° to 75°. Figure 17 shows an example of this procedure. From the results, we can see that when the degree reach to around 75°, the result image become blurry and the characters are extremely hard to recognize by the program.

Image binarization

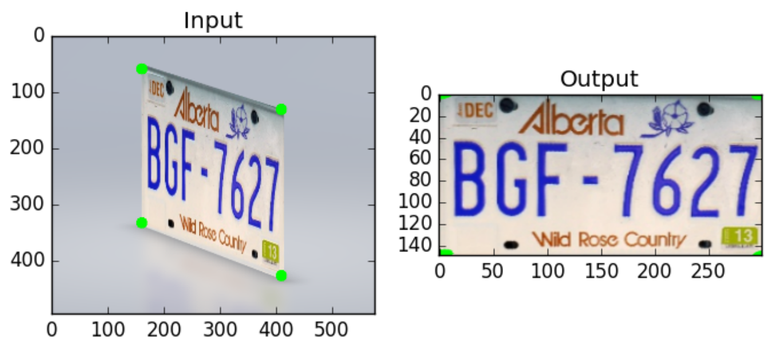
Image normalization, also known as the image binarization, is one processing stage for character recognition, and also can separate foreground from the background [6]. An ideal text image can be extracted through the binarization procedure, in which the characters are in white, and background with complicated objects is in black. Numerous binarization methods have been proposed over past ten years or so. Among them, there are four methods, which can obtain a good result for recognition.

1. Adaptive method. In this algorithm, threshold value is calculated for a small regions of the image. Different regions has different threshold values. "Threshold value is the weighted sum of neighbourhood values where weights are a gaussian window." [30]

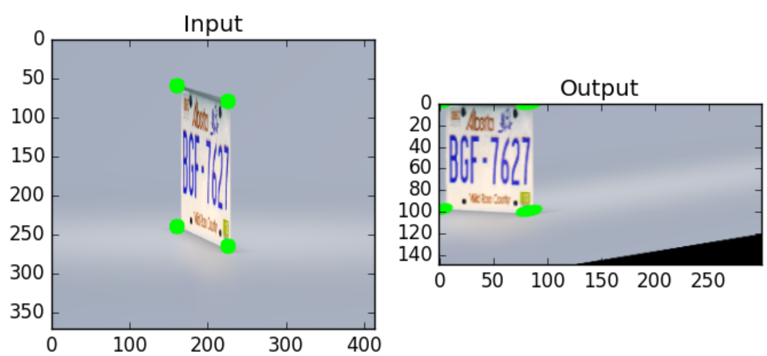
2. Niblack's Algorithm [27]. This algorithm "calculates a pixel-wise threshold by



(a)



(b)



(c)

Figure 17: Comparison of transformation procedure with different degrees, 30°, 60° and 75°

sliding a rectangular window over the gray level image." [21] The computation is given by the equation below:

$$T_{Niblack} = m + 0.2 * \sqrt{\frac{1}{NP} \sum (p_i - m)^2} \tag{16}$$

where m is mean value of the pixels p_i, NP is the number of pixels in the image.

3. Sauvola's Algorithm [39]. It is modified algorithm from Niblack's Algorithm.

$$T_{Sauvola} = m * (1 - 0.5 * (1 - \frac{s}{128})) \tag{17}$$

where m is mean value of the pixels, and s is the standard deviation.

4. Wolf's Algorithm [47].

$$T_{wolf} = (1 - k) * m + k * M + \frac{k * s}{R}(m - M) \tag{18}$$

where k is set to 0.5 by authors in [wolf2004extraction], m is the mean value of the image, M is the minimum gray value of the image and R is set to the maximum gray value. Standard deviation is obtained over all the local neighborhoods.

Figure 18 is an original license plate image for binarization used in our test. Figure 19 is the comparison of four binarization methods. From the results, we cannot find which method is the best since the image we captured is good in quality. However, when we select a blurred or low quality license plate image, we can see that the results. Figure 20 is the original image. Figure 21 is the comparison of four binarization methods with a blurred image. From our experiments, we conclude that the Wolf algorithm is better than the other three approaches. Hence, from previous work [21] and our own tests, the Wolf Algorithm appears to be the best approach for our system.

Figure 18: A clear original License plate image

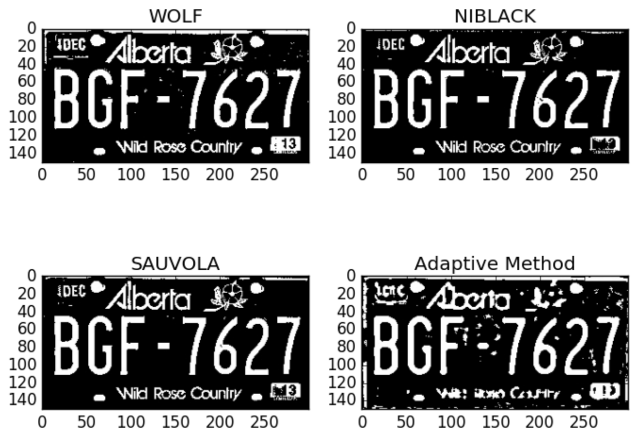


Figure 19: Comparison of different binarization methods on a clear image

Figure 20: An original blurred License plate image

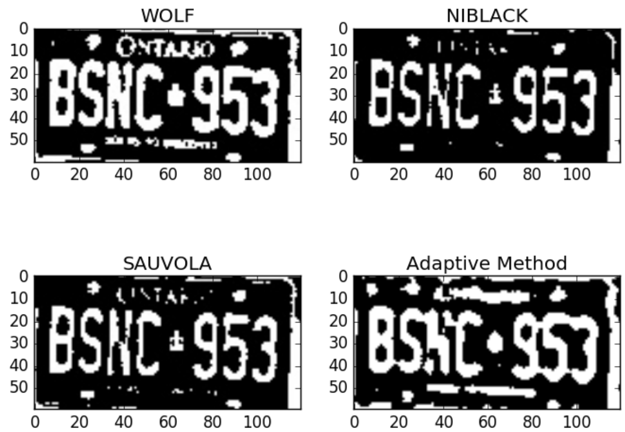


Figure 21: Comparison of different binarization methods on a blurred image

Character bounding box detection

To obtain a better result for recognition, the province label before the characters and the tag line after it should be removed from the processed license image from the previous step. Therefore, with the binarization image extracted, we can detect contours which can be explained simply as a curve joining all the continuous points (along the boundary), having same color or intensity [31] . Our procedure takes contours as one tool for character analysis and text line detection. The following Figure 22 is an example of contours detection. In this phase, all contours in the license plate image are detected by the system. However, the contours that we need is those around the characters. Therefore, the small contours above the numbers and below numbers are filtered through one method. In this method, bounding rectangle algorithm [36] can be used to find minimal up-right rectangle for the specified point set. For computing the minimum height of the rectangle, we find a relationship between character height and plate size from our dataset:

$$0.3 * H_{plate} < H_{character} < 0.9 * H_{plate} \tag{19}$$

Figure 22: Procedure for contours detection

Figure 23: Procedure for contours filter and text line detection

where H_{plate} is the height of the license plate and $H_{character}$ is the height of the characters. Hence, if the height of bounding rectangle is smaller than H_{plate}, all the contours in it will be removed. Consequently, a couple of text lines are determined by the program. The Figure 23 presents the example of text line detection procedure.

3.2.3 Character segmentation

Character segmentation is an operation that attempts to decompose an image of a sequence of characters into individual ones [5]. As one preprocess of character recognition, its result can highly affect the performance of recognition. In this stage, characters separation method is used in the image extracted from previous stage. As a result, the individual character are obtained from character segmentation phase to carry out the process of identification.

In our system, to isolate all the characters, histogram calculation is used to find gaps in the plate characters. Histogram is a plot which can describe the intensity distribution of an image, in which X-axis denote the column of the image which is from 1 to the width of the image, and Y-axis represent number of the pixel which is not 0 in the current column. With the histogram obtained, the gaps between

Figure 24: Procedure for character segmentation

characters are detected, which determine the bounding box for each symbol in the license plate. Figure 24 is an example of character segmentation procedure.

3.2.4 Character recognition

Character recognition, popularly referred as Optical Character Recognition(OCR) is a very important stage in the proposed system. OCR is the automatic process of converting typed, handwritten, or printed text to machine-encoded text that we can access and manipulate via a string variable. In recent decades, with the development of the computer vision techniques, the OCR has been one of the challenging and popular fields of research in pattern recognition. Serval methods have been proposed, such as template-matching and structure analysis method.

Nevertheless, we can take OCR as one of the classification problem in the image processing step, since the most crucial step in OCR is identifying characters as one of 36 symbols (A-Z and 0-9). Therefore, for classification, we need to extract visual features from individual character image.Then, character can be classified with these features using machine learning. The most effective way for now is OCR-tesseract, which is originally developed by Hewlett Packard in the 1980s. It is one of the most accurate open source OCR engines currently available. As other traditional procedures, this processing follow a step by step approach. As the most important part, recognition consists of two stages, which are adaptive classification and repeating recognition, respectively. In the first stage, each character is recognized sequentially. Additionally, the symbol that is classified is stored by the adaptive classifier as the training data. Then, the adaptive classifier will learn the information that classified characters provide, from which the characters that are not recognized in first step will

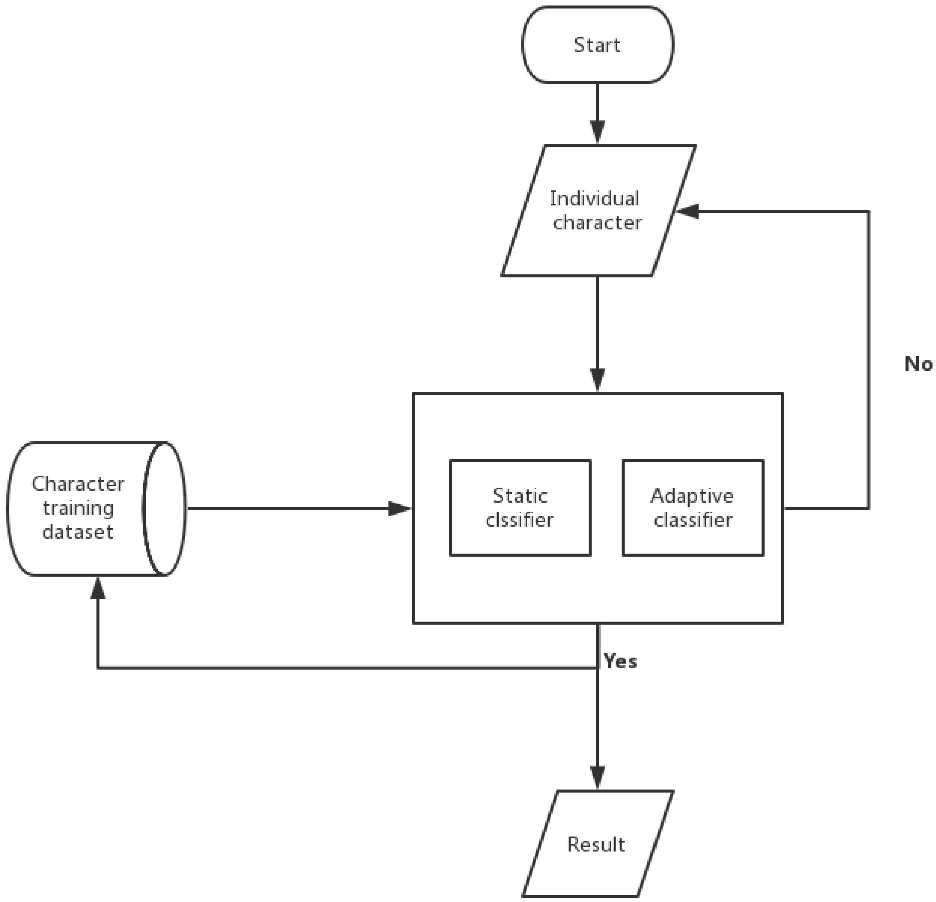


Figure 25: Flowchart of OCR process

be classified again. This two-stage process make this method accurate and efficient. The Figure 25 is the flowchart of the OCR approach.

Finally, the above five main stages build up our proposed ALPR system. However, as we discussed before, only license plate information cannot correctly detect and identify the vehicle. Hence, in next two parts, we introduce the province detecting system and vehicle type classification system.

3.3 Province detection

In most provinces in Canada, there are tag lines to describe the province on the license plate. In contour detection phase, we use a filter function to discard the small contours, which may be in the tag lines. Therefore, in this processing, what we need to test is the plate extracted just from the license plate detection procedure. Since the character of the province name is too small to recognize in the license plate image, the features of the symbol of the province need to be taken into consideration.

A feature is a piece of information that can describe the image, such as edges, corners, blobs and ridges. Generally, features are used as a starting phase for may computer vision algorithms, which is known as feature detection. Feature detection is a procedure for determining whether the given image features can be found in other images. Hence, the detected features become a key to find other images which have the same features.

In our proposed system, the character area has been detected by the contours detection phase, which stands below the tag lines. Therefore, the tag lines can be determined, which is located in the top or the bottom of the plate. Next, to detect the feature, FAST (Features from Accelerated Segment Test) algorithm [35]will be used. Other detectors do well in performance, such as SIFT (Scale-Invariant Feature Transform) [25] and SURF (Speeded-Up Robust Features) [3]. However, in a real-time application, time complexity is one of key point which need to be taken into consideration. FAST, which keeps good performance in detecting features, is several times faster than other existing feature detectors. The following lists the steps of the feature detection.

1. Select a pixel p from the province area and its intensity I_P
2. Threshold value t will be set manually. In our system, the value is chosen as 5, which can make the program more sensitive to the corners in a image.
3. 16 Surrounding pixels are determined as one set G.
4. If there is a set of more than 11 contiguous pixels in G which are all brighter

than $I_P + 5$ or all darker than $I_P - 5$, p is determined as a corner.

5. Among the 16 pixels, four of them are tested, which are above, below, left and right the pixel, respectively. If p is a corner, then at least three of these must all be brighter than $I_P + 5$ or darker than $I_P - 5$. If neither of these is the case, then p can not be the corner.

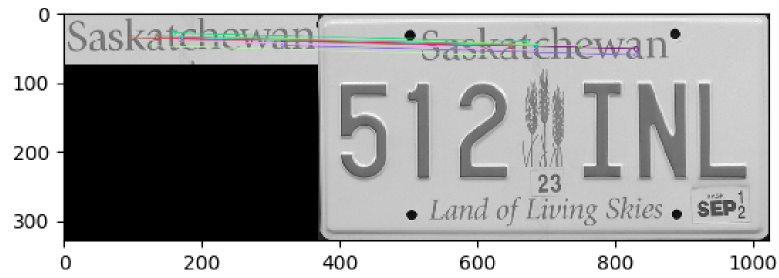
The limitation of the program is that the algorithm is not robust if there exist high levels of noise in the image. Additionally, the threshold can not be determined automatically, which means, inappropriate threshold value will lead to slow speed and poor performance in the test.

After that, with the extracted features, we need to use one approach to match the image that we test. Hence, Brute-Force Matcher is used to match the features between training dataset and testing images. Initially, the matcher will store the features of training images into one dataset. Then, the descriptor of one feature is matched with the test image via distance calculation. Finally, the name of the province is obtained by searching the smallest distance value.

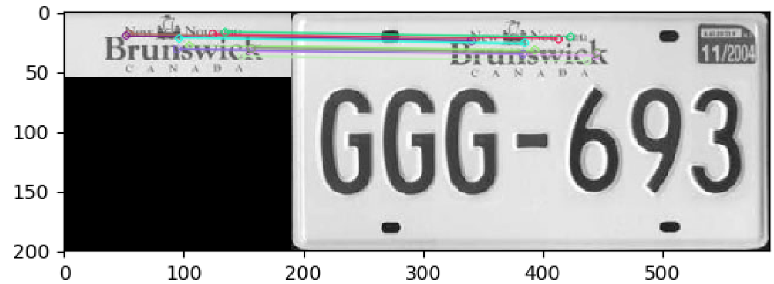
3.4 Vehicle shape detection and recognition

In our system, the camera is active when the vehicle come to the monitoring area such as entry lane of the parking facility. To detect the vehicle, LBP, HOG, and Cascading classifiers are employed as the same way for the plate detection.

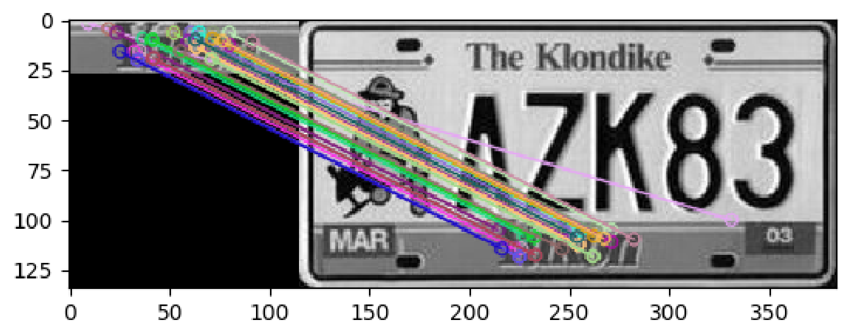
In this phase, the result that we want to derive is the type of the vehicle, such as SUV, pickup or sedan. Therefore, the task can be considered as image classification, which assigns an input image one label from a fixed set of categories. In machining learning, extracting features of the object are indispensable part of procedure. However, in vehicle categorization program, it is extremely hard to get useful features without noise from the image with various illumination. Histogram of oriented gradients (HOG), Region-based Shape Descriptor (RSD), Edge Histogram Descriptor (EHD) can be used as the feature descriptors to detect object instead of classification



(a)



(b)



(c)

Figure 26: Feature matching examples

because similar objects have so closed feature descriptors that normal classification cannot classify them with high accuracy. Therefore, Neural Networks are employed in the procedure, which can progressively improve performance by considering examples. Additionally, among them, convolutional neural network (CNN) is the best approach in image processing application.

CNN, which is very similar to ordinary Neural Network, consists of a serval neurons that have learnable weights and biases. In the procedure, each neuron receives some inputs, performs a dot product and follows it with a nonlinearity. Meanwhile, unlike regular neural networks, the layers of CNN have neurons arranged in 3 dimensions:

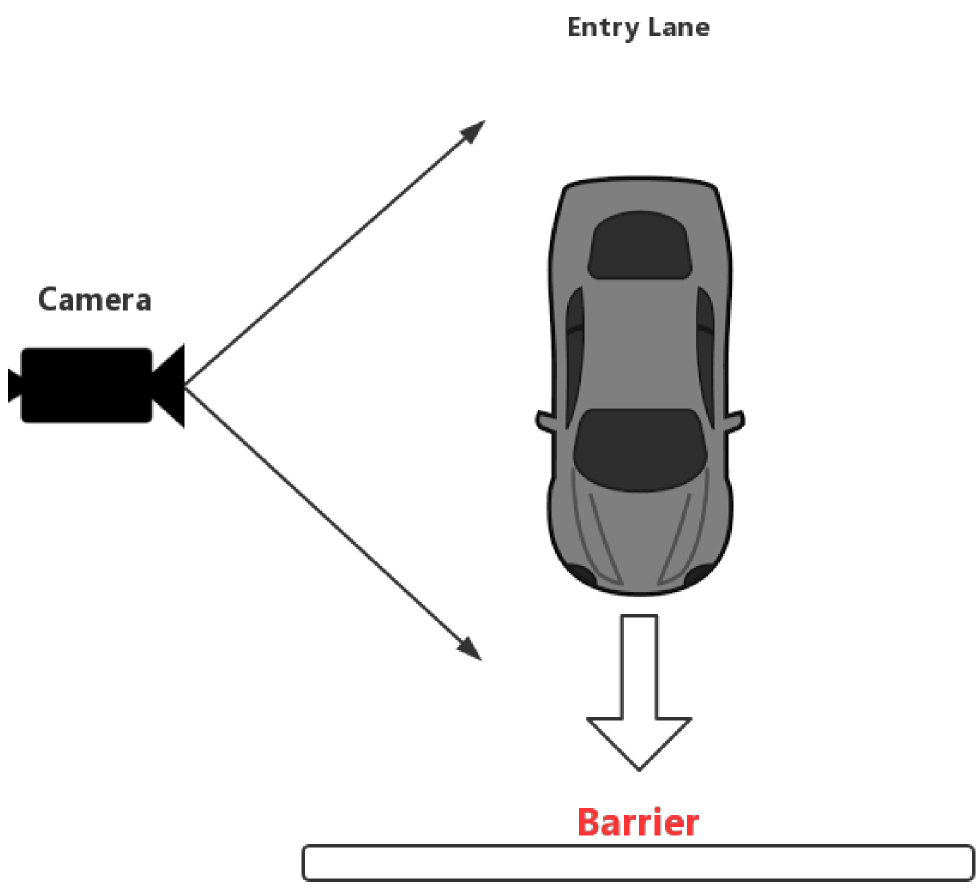


Figure 27: Camera position for vehicle shape recognition

width, height, depth. Therefore, in our system, the vehicle image of side view captured from the camera, its width and height would be the dimension of the image, and the depth would be 3 (Red, Green and Blue). In CNN architecture, four layers are employed for training data and performing a test. Fig28 shows the classification result of CNN.

1. Convolutional layer. Each neuron in it computes a dot product between and a small region of the vehicle image

2. Rectified Linear Units (RELU) Layer. It will apply a thresholding function.

3. Pool layer. Pool layer will perform a down-sampling operation.

4. Fully Connected (FC) Layer. It will compute the class score.

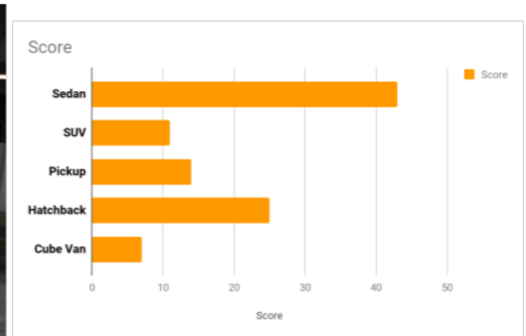


Figure 28: Result of classification using CNN

After vehicle detection and recognition, the system can identify the vehicle along with the license plate number and province information. In detail, when the license plate number is derived by ALPR system, the machine will search the database with the number to get the information of the vehicle. The information is the license plate's registration province and the vehicle's shape type. Comparing the information with the result computed from province detection procedure and vehicle shape detection and recognition procedure, we can find whether the vehicle is legal or not and determine whether the plate is affixed on another vehicle.

3.5 Evaluation

To evaluate the results of our system, accuracy will be set to the benchmark. It can be calculated by following formula:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{20}$$

where TP is the number of true positive samples and ALL is the number of all samples, TN is the number of true negative samples. TP and TN are the number of samples which are classified correctly by some methods. False positive and false negative are the number of samples which are classified incorrectly.

Specifically, in license plate detection system, there are no negative samples in the dataset, which means every image contains a license plate. Hence, the accuracy of the detection system should be calculated by following formula:

$$Detection\_accuracy = \frac{\text{The number of detected license plates}}{\text{The number of all license plates}} \tag{21}$$

In recognition system, accuracy for character recognition is calculated by below formula:

$$Recognition\_accuracy = \frac{ncr}{N} \tag{22}$$

where ncr is the number of characters which are recognized correctly. N is the number of all characters in the dataset.

The accuracy of the whole system is derived by following formula:

$$Recognition\_accuracy = \frac{ncp}{N_i} \tag{23}$$

where ncp is the number of the image, in which the license plate is detected and each character is recognized correctly. N_i is the number of all images in the dataset.

In license plate detection and vehicle shape detection and recognition, Cross-validation[22] is used to evaluate the methods. It is a model validation for estimating how good a classification model will perform in practice. In our system, 10-fold cross validation is considered as the main function for evaluation. In the method, our image dataset is divided randomly into 10 disjoint sets of equal size. Next, our classifier is trained 10 times. At each time, one of the 10 groups is left out for testing. The other 9 sets are used for training. Finally, we can derive 10 error rates. Mean error rate is computed by below formula:

$$er = \frac{e_1 + e_2 + e_3 + \cdots + e_{10}}{10}, \tag{24}$$

where er the mean error rate and e_i is the error rate obtained by each training procedure.

CHAPTER 4

Result and discussion

4.1 Platform and hardware

1. Developing language: python with OpenCV,
2. Operation system: ubuntu 16.04 LTS
3. CPU: 1.6GHZ Inter Core i5
4. Memory: 4GB, 1333MHz DDR3

4.2 Input

For evaluation of the our system and comparison with other approaches, vehicle images captured by the entrance of a public parking garage are used both for training and testing. The dataset contains 500 images of resolution 1280×720. We have extracted license plate image from the each image. Then the program extracts LBP and HOG features from the them, which are for detection. For vehicle shape classification, cars dataset from [23] are used as training image dataset of CNN. In the dataset, we group all of the images into four classes, which are sedan, SUV, pickup and hatchback. With the four groups, we build a model to recognize the type of vehicles. For testing, a collection side-view images from a parking garage are used.

4.3 Procedure of system

The images given below provide the screenshots of the proposed scheme methodology and results simulated by ALPR system, province detection system and vehicle shape detection and recognition system. Figure 29 shows a testing image from the dataset. As can be observed, the image is captured in angle and as a result, license plate is not straight.

When the vehicle come to the entrance of parking lot, the camera activate to capture the front plate of the vehicle. Figure 30 - Figure 34 present the procedure of license plate detection and extraction.

Figure 29: Input image captured in a Parking lot

Figure 30: Gray scale conversion of the captured image

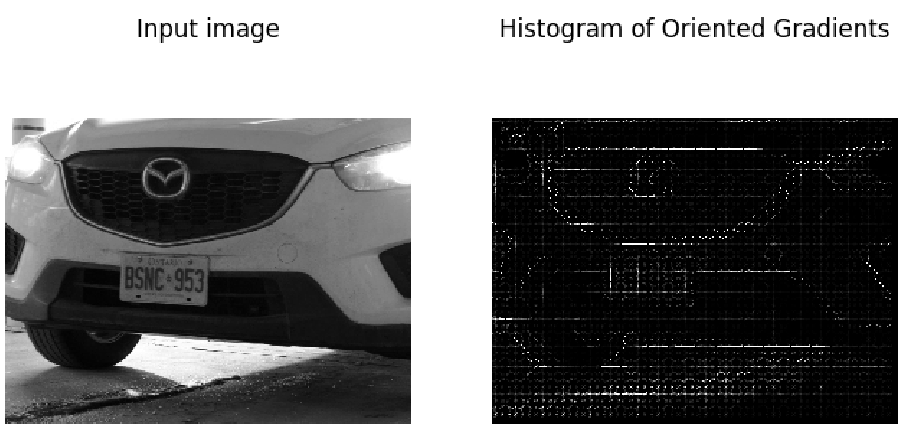


Figure 31: HOG conversion of the gray image

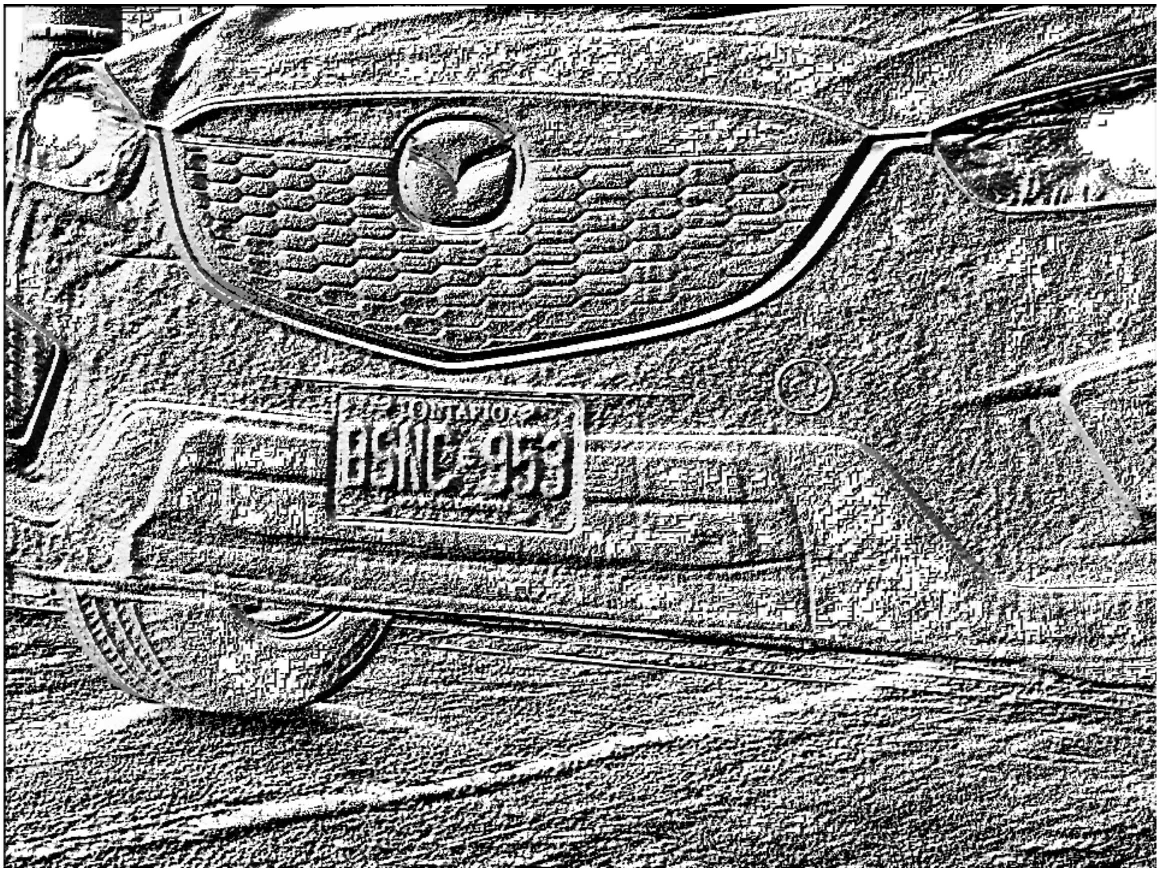


Figure 32: LBP conversion of the gray image

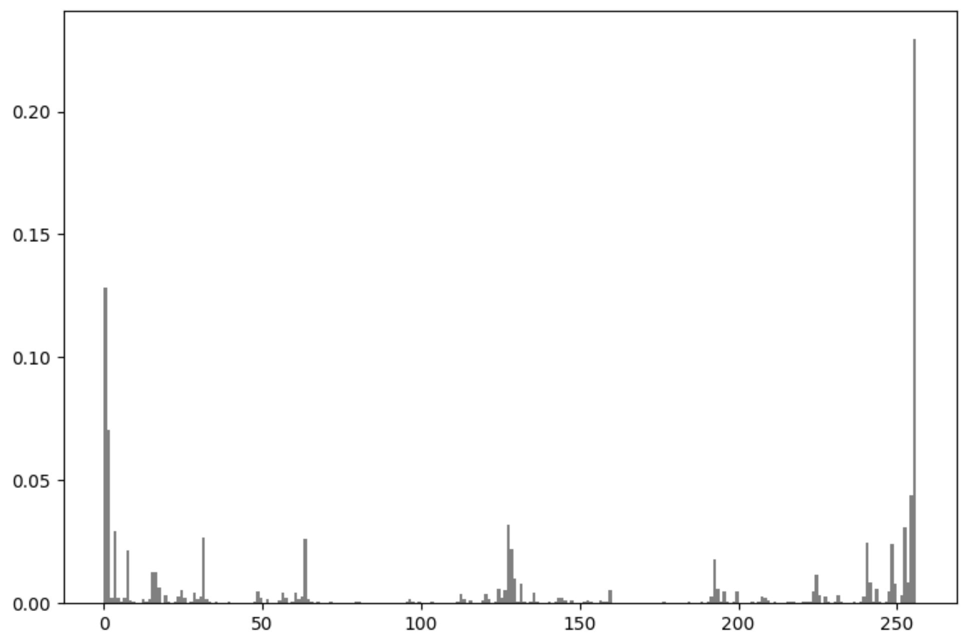


Figure 33: Histogram of LBP image

Figure 34: License plate extraction from the image

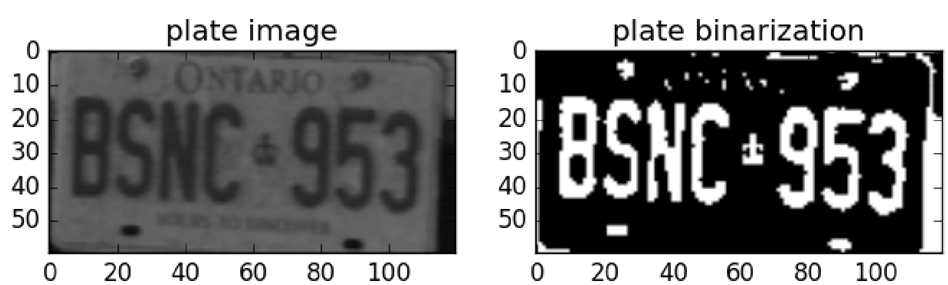


Figure 35: License plate image binarization

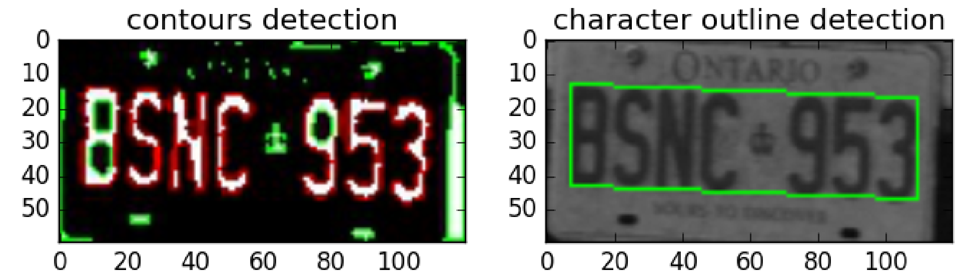


Figure 36: Contours filter and text line detection

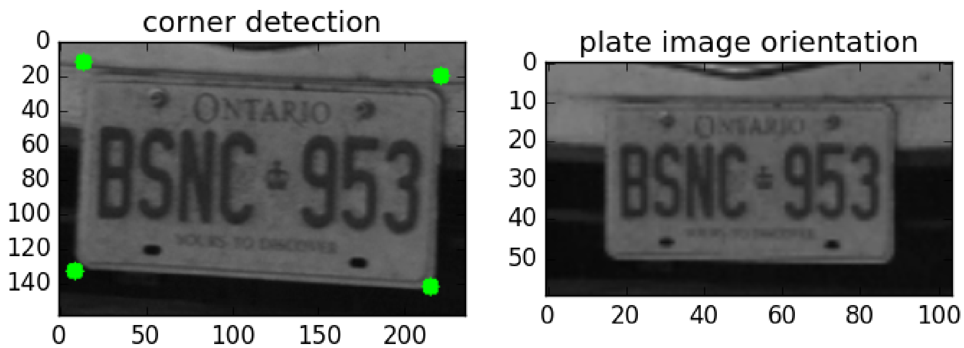


Figure 37: License plate orientation

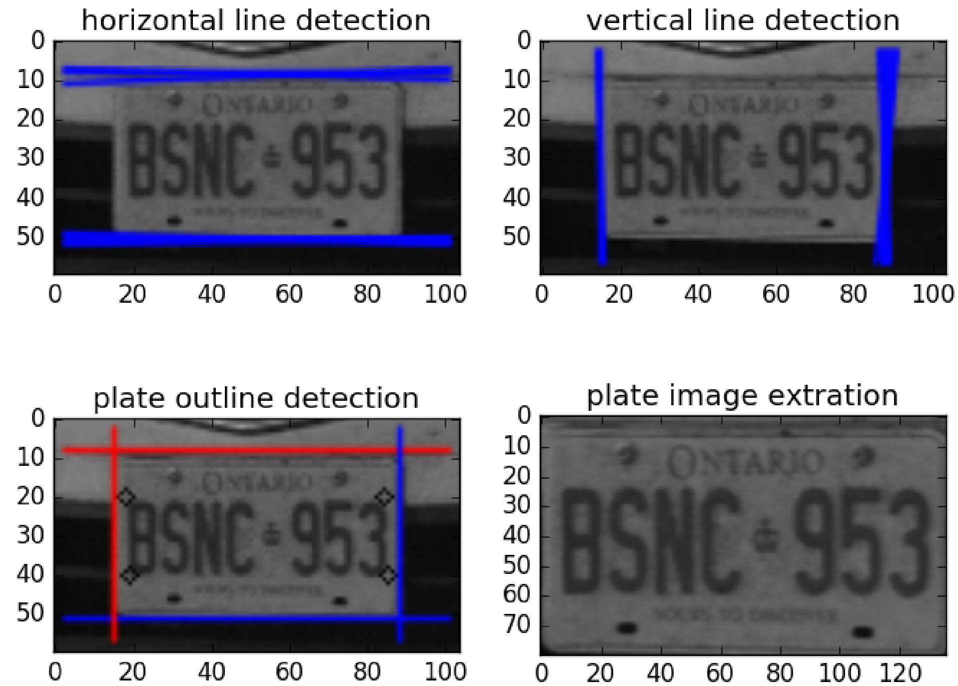


Figure 38: Processing of plate image

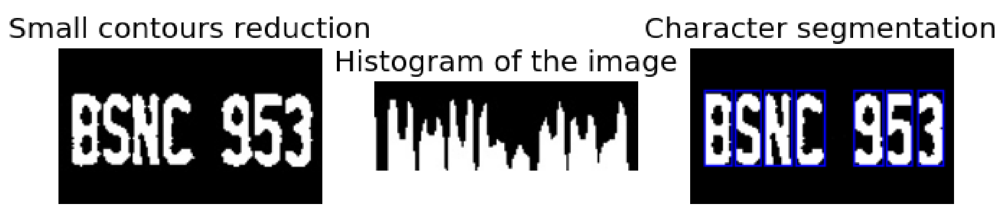


Figure 39: Character segmentation

4.4 Evaluation and comparison

Table 2: Part of results derived by the system

No	Input licnese plate number	Plate detection	Result	PROVINCE
1	BFNR598	Yes	BFNR598	Ontario
2	AZHB448	Yes	AZHB448	Ontario
3	BSNC953	Yes	BSNC953	Ontario
4	BAMP606	Yes	BAMP606	Ontario
5	BEMR927	Yes	BEMR927	Ontario
6	BVMC396	Yes	BVMC396	Ontario
7	AKRS042	yes	AKRS04	Ontario
8	BSYF779	Yes	BSYF779	Ontario
9	BSYN873	Yes	BSYN873	Ontario
10	BVBJ301	Yes	BVBJ301	Ontario
11	BVLV755	Yes	BVLV755	Ontario
12	ATEP757	Yes	ATEP757	Ontario
13	BYWC112	Yes	BYWC112	Ontario
14	ASAH185	Yes	ASAH185	Ontario
15	BLHB815	Yes	BLHB815	Ontario
16	WZ1100	Yes	HZ1100(wrong)	Ontario
17	BKWW841	Yes	BKWW841	Ontario
18	BVNK986	Yes	BVNK986	Ontario
19	BNTC360	Yes	BNTC360	Ontario
20	BHHK873	Yes	BHHK873	Ontario

The Table 2 shows some of the results that come from our ALPR system and province detection system. From the table, there is a sample in which the system get a wrong result of character recognition. The original image Figure 40 is showed below. There is a shadow region in the license plate of the image. Hence, the character "W" is recognized as "H".

Figure 40: The characters of the license plate is recognized incorrectly

With the same dataset, we use other three approaches to detect the license plate from test images. 10-fold cross validation is employed to derived the success rate of each method. The Figure 41 presents the results of each algorithm.

The comparison illustrates that our approach, in which LBP and HOG are extracted features and AdaBoost is the classifier, is better than other approaches. Additionally, from Table 3, we can see the required time of our approach is very close to LBP+Cascade. But the accuracy of our approach is higher than LBP+Cascade. Figure 42 illustrates the accuracy of OCR for all characters in 500 images. Figure 43 shows the final result of the automatic license plate recognition system. In these 500 images, there are 10 images in which the license plates are not detected. Meanwhile, there are 17 images in which some characters are recognized incorrectly. Hence, the accuracy of the proposed system is 94.6%.

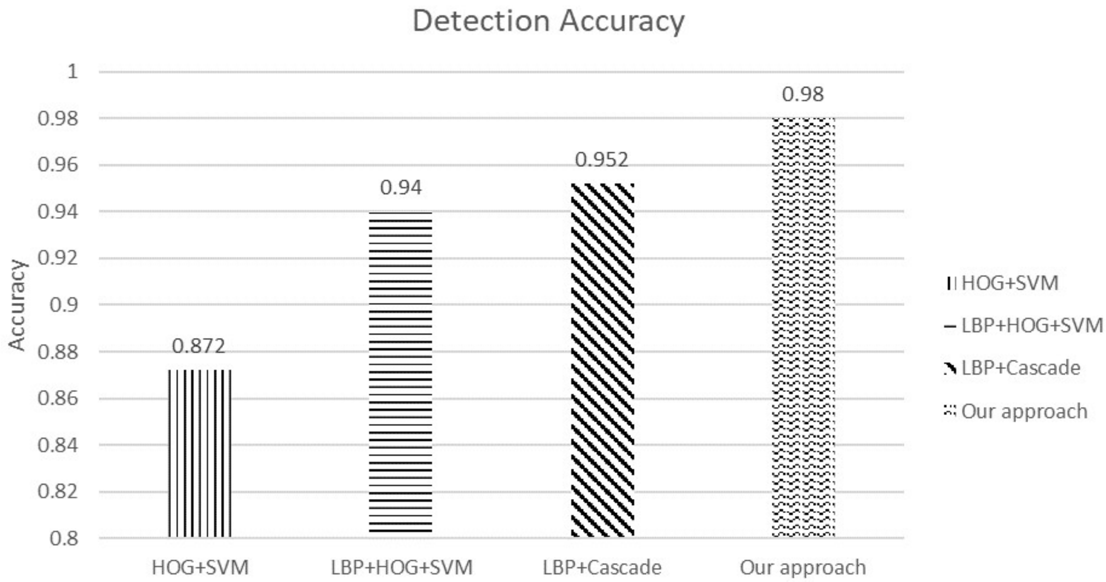


Figure 41: Comparison of detection methods

Table 3: A comparison of the time required

Approach	Time
HOG+SVM[9]	0.923sec
LBP+HOG+SVM[46]	0.987sec
LBP+Cascade[48]	0.335sec
Proposed approach	0.343sec

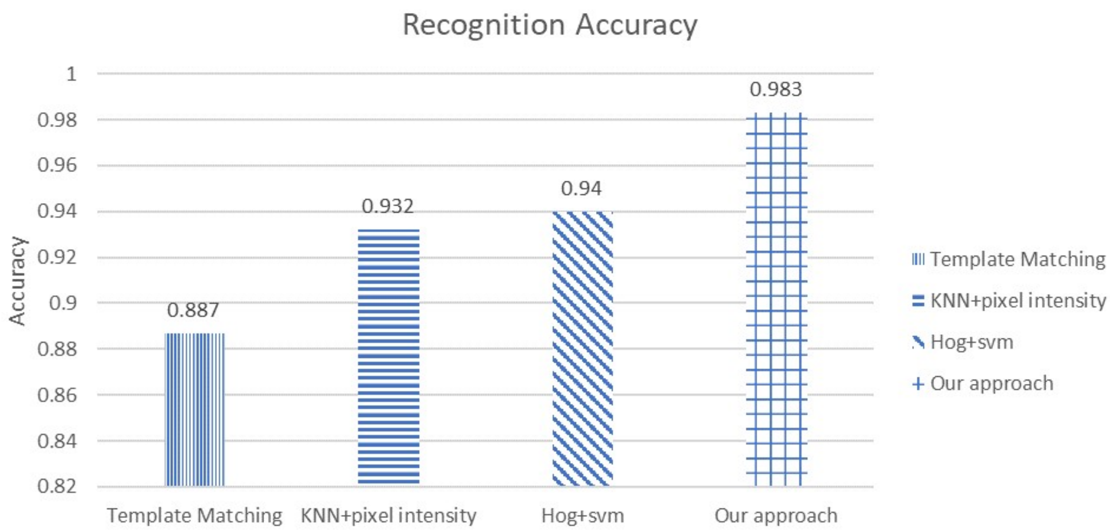


Figure 42: Comparison of OCR methods

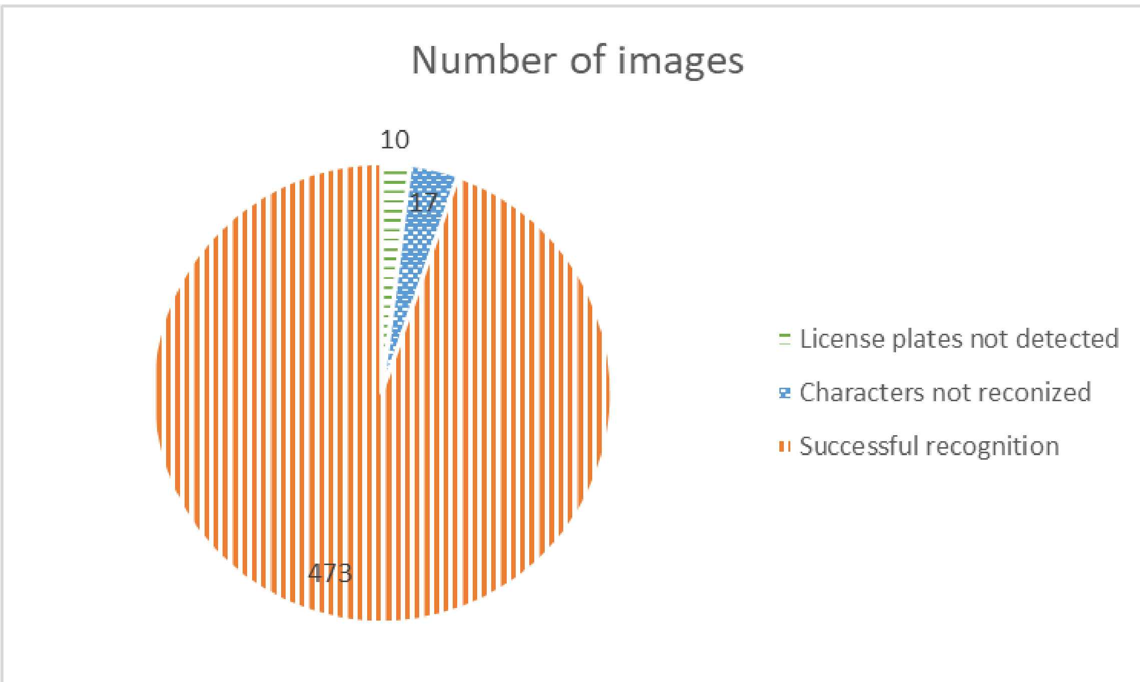


Figure 43: Result of the proposed system

In most cases, the proposed system can detect the license plate and recognize the characters correctly. In Figure 44, there is a background in one Michigan license plate, which may affect the performance of the recognition. However, this system can recognize all characters on the license plate successfully. Actually, the binarization method can remove the background image without any affection for the characters. In another case, we add a noise line on the license plate. The Figure 45 shows the procedure of the recognition. The proposed system can detect the plate and can recognize each character correctly.

Figure 44: The license plate with a background

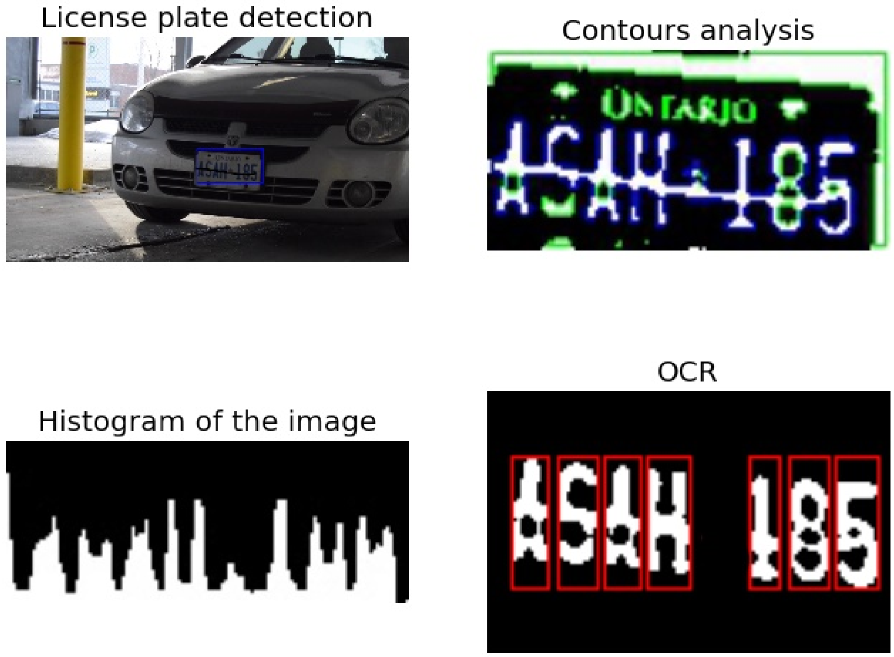


Figure 45: The license plate with a noise line

The Table 4 and Figure 46 presents the result of CNN classification. The number of input images is 200. In the test, only 6 Hatchbacks are classified as SUV or sedan. The accuracy of the system is 97%. The outline of a Hatchback sometimes is similar to the sedan or SUV. Figure 47 shows an error example. From the image, we can observe, the scores of sedan, SUV and hatchback are extremely closed. Actually, the training dataset for CNN should be large enough for learning and training. However, The dataset of the proposed system is not that large, which could affect the result score of each vehicle type. In the future, any input image can be added into the training dataset for improving the accuracy of the system.

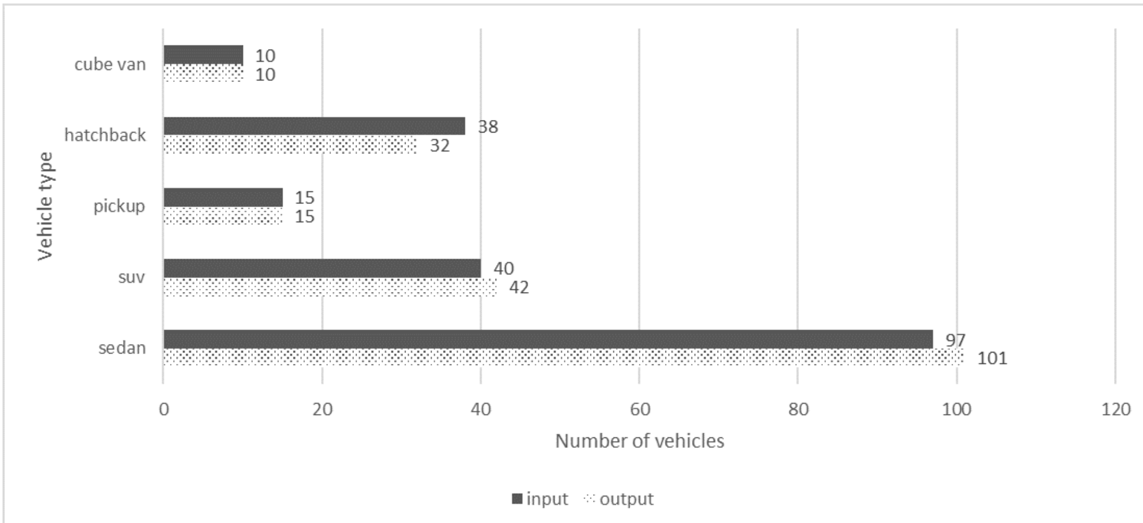


Figure 46: vehicle shape classification

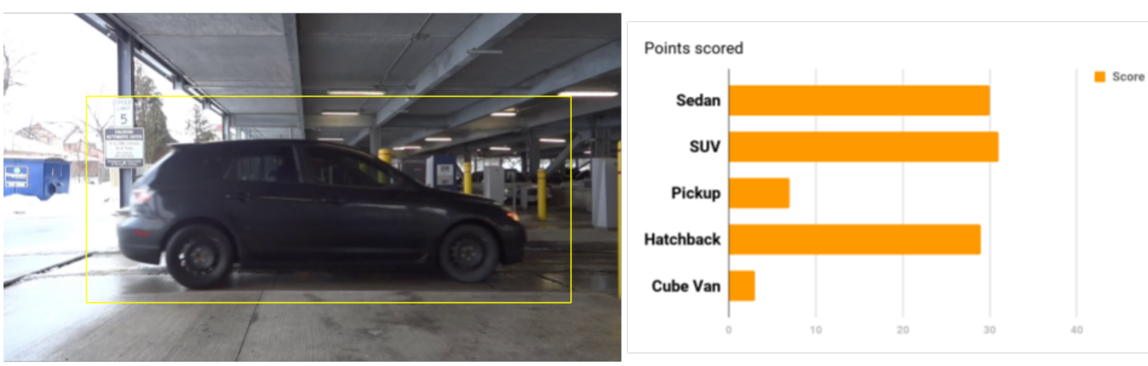


Figure 47: A hatchback misclassified as SUV

Table 4: Vehicle shape classification

Vehicle type	input	output
Sedan	97	101
SUV	40	42
Pickup	15	15
Hatchback	38	32
Truck	10	10

CHAPTER 5

Conclusion

We proposed a new feature-based method to recognize license plate number with high accuracy. To extract features from the image, we convert it into LBP and HOG. It is extremely effective to detect the license plate due to the high accuracy in our test. The cascade methods are employed to speed up to localize the license plate in the original image. Some preprocessing approaches such as image orientation, image character analysis and image binarization are undoubtedly good for the performance of character segmentation and recognition. As the most crucial part, character recognition with adaptive classifier, is organized and modified in our system. Therefore, the procedure are more efficient and accurate.

Another contribution of this research is to find a strategy to detect the province and vehicle shape from the image. Character recognition cannot be used to recognize the province label and character since they are too small. Feature matching methods are employed to match the testing image contours with other images in the database. This enhances the overall performance of the detection.

After getting all the results, we find that the performance of our approach is better than others. Using feature matching to detect province is the best choice. In vehicle shape detection and recognition, the accuracy of CNN is relatively higher in most conditions. However, there are some cases where the vehicle shape are very hard to recognize. For example, shapes of some hatchbacks are very closed to those of SUV. Hence, the size of training dataset play an important role in the system. The proposed system is designed and tested for the front license plates of vehicles. However, in serval states and provinces in USA and Canada like Delaware, Florida, Georgia, Alabama, Arizona, Michigan and so on, putting a license plate on the front bumper is illegal [33]. Consequently, the proposed system cannot be used for vehicles from these states or provinces. Hence, in the future, to modify the system, we can add another camera for capturing the back license plates.

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