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General Introduction

Vehicle identification is a research area where image processing methods are used to identify vehicles by detecting and identifying the license plate numbers. Typical vehicle identification systems consist of three main stages. They are: locating the license plate, accurately identifying the numbers in the license plate and the identification of vehicles.

Although many intensive research studies have been conducted in other countries in the area of automatic vehicle identification, to our knowledge, there is virtually no research studies conducted in Algeria in this area. However, vehicle identification is an essential area in the development of intelligent traffic systems and surveillance. Given the current security situation in the country due to ethnic conflicts, this is one of the areas where there is an urgent need for the development of devices that could be used in variety of situations to ease the security concerns. In addition, the use of vehicles in Algeria has increased rapidly due to urbanization and modernization, especially in recent years, and thus, traffic congestion in cities has become a major issue due to inadequate road infrastructure. Therefore, control of vehicles and identification of traffic violators to maintain discipline, is becoming a big problem in many cities. Automatic vehicle identification systems can be used effectively for this purpose.

The recognition problem is generally sub-divided into two parts are:

- Number Plate Variations can be one of the given below: location: plates exist in different locations of an image, size: plates may have different sizes due to the camera distance and the zoom factor, color: plates may have various characters and background colors due to different plate types or capturing devices.
- Environmental variations: Illumination: input images may have different types of illumination, mainly due to environmental lighting and vehicle headlights, Background: the image background may contain patterns similar to plates, such as numbers stamped on a vehicle, bumper with vertical patterns, and textured floors, for example, in Algeria the norm is printing the license plate number in black colour on white background for front of vehicles and on a yellow background for back of vehicles. Number plate is a pattern with very high

variations of contrast. If the number plates is very similar to the background it's difficult to identify the location, Brightness and contrast is changes to it. The morphological operation reused to extract the contrast feature within in the plate

The objective is to present architecture of ANPR (Automatic Number plate recognition system) by invariant moments to extract the parameters of discrimination and supporting vectors machine as classifiers.

This work includes four chapters, which allow us to present the various aspects of our work.

The first chapter will be devoted to plate registration, firstly present a general of the plate overview and historic, we will present them later in Europe, Africa and Asia the number plate and the description of the different series of license plate in the Algeria (Normal and special series).

We will present in the second chapter the general architecture and the various stages that make up the process of recognition of the license plate in general. We will present the most frequently cited techniques used at the every stage of Automatic Number plate recognition (ANPR) system (Image Acquisition Vehicle Image Pre-Processing, Extraction License Plate, License plate Pre-Processing, Character Segmentation and Character Recognition) and includes some works already done on this system by various researchers using different methodologies and algorithms.

In chapter three, we will discuss the classification method particularly well suited for treating high dimension data (support vector machine SVM).

In chapter four, we will first present the development environment and the different algorithms used. We present in this chapter a detailed description of the license plate recognition system, which includes six major phases: the vehicle image acquisition, preprocessing of the vehicle image, license plate extraction, preprocessing on the license plate character segmentation, and character recognition. Then we will present the experimental results obtained for each stage of the system made and the different discussion about these results.

We will finish the work with a conclusion and perspectives for future work in this research area.

Chapitre 1

generalities on license plate

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1.1 Introduction

A license plate is a plate with a unique combination of numbers or letters (for a given geographic area), for easy identification of a land vehicle (car, motorcycle, agricultural vehicle, etc.).

will be devoted to plate registration, firstly present a general of the plate overview and historic, we will present them later in Europe, Africa and Asia the number plate and the description of the different series of license plate in the Algeria (Normal and special series).

1.2 Definition

A vehicle registration plate is a metal or plastic plate attached to a motor vehicle or trailer for official identification purposes. The registration identifier is a numeric or alphanumeric code that uniquely identifies the vehicle owner within the issuing region's database. In some countries, the identifier is unique within the entire country, while in others it is unique within a state or province. Whether the identifier is associated with a vehicle or a person also varies by issuing agency. Depending on the country, the vehicle registration plate may be called a license plate (United States, Canada), or number plate (India, United Kingdom, Australia).[1]

1.3 History of license plate

License plates have been around for longer than there have been automobiles. France was the first country to introduce the license plate with the passage of the Paris Police Ordinance on August 14, 1893, followed by Germany in 1896. The Netherlands was the first country to introduce a nationally registered license plate, called a "driving permit", in 1898.

Initially these plates were just sequentially numbered, starting at 1, but this was changed in 1906.

In the U.S., where each state issues plates, New York State has required plates since 1903 (black numerals on a white background) after first requiring in 1901 that only the owner's initials be clearly visible on the back of the vehicle. At first, plates were not government issued in most jurisdictions and motorists were obliged to make their own. In 1903, Massachusetts was the first state to issue plates. UK plates were first required from 1 January 1904 by the 1903 Motor Car Act.

The earliest plates were made of porcelain baked onto iron or ceramic with no backing, which made them fragile and impractical. Few of these early plates survived. Later experimental materials include cardboard, leather, plastic, and, during wartime shortages, copper and pressed soybeans.

Early 20th century plates varied in size and shape from one jurisdiction to the next, such that if someone moved, new holes would need to be drilled into the automobile's bumper to support the new plate. Standardization of plates came in 1957, when automobile manufacturers came to agreement with governments and international standards organizations. While peculiar local variants exist, there are three basic standards worldwide.[1]

Figure 1.1 The first best saved license plate.

1.4 License plate

1.4.1 License plate in Europe

In the European Union, white or yellow number plates of a common format and size are issued throughout, although they are still optional in some member states. Nevertheless, some individual member states still use differing non-EU formats - Belgium, for example, still permits vehicles to display the older small white number plates with red lettering, and the license plates that are issued by the government body which assigns these are of the smaller format, too. In 1908 number plates were only 3 numbers and 1 letter long. Italy still permits smaller plates to be attached to the front of a vehicle, while the rear plate complies to the usual EU format. The common design consists of a blue strip on the left of the plate, which has the EU motif (12 yellow stars), along with the country code of the member state in which the vehicle was registered.

Lettering on the plate must be black on a white or yellow reflective background. With this EU format, vehicles are no longer required to carry an international code plate or sticker for traveling between member states. The non-EU states of Switzerland, Norway and Turkey also recognise the blue strip instead of the traditional white oval with the country code in black.

Diplomatic plates are usually denoted by the letters "CD" in Europe which stands for Corps Diplomatic located usually at the beginning of the number plate (France, Belgium) or middle (Netherlands). The United Kingdom uses "D" for "diplomat"[1].

Country	Example
Russian Federation	
Denmark	
Finland	
Turkey	
Ukraine	

figure 1.2 license plate of some European countries

1.4.2 Number Plates in Africa

Africa is a large and diverse continent, so as you may expect, they have a huge variety of different licence plates depending on where you are. Here's how the number plates look in countries in Africa with the largest number of vehicles[2]:

Algeria: number plates here consist of ten digits split into a XXXXX XXX XX format. The second block of numbers shows whether it is a private or commercial vehicle and the date of registration.

Angola: plates follow a LLL DD DD format which has been used since 1973.

Egypt: these number plates use Arabic characters for digits and letters. They also use different colours to signify the type of vehicle police use blue plates with red and white lettering while private vehicles are white plates with black lettering.

Ghana: follows a LL DDDD L format to mark their plates, but there can be less than four digits used.

Kenya: use a plate that looks similar to the UK suffix style registrations with the format LLL DDDL.

Libya: these plates have the digits written in Arabic and English and follow a DD D DDDD format.

Morocco: plates use a DDDD – DD format with the last two digits showing where the vehicle was registered.

Tunisia: have a combination of Arabic and English characters, typically using a selection of digits and finishing in an Arabic character.

1.4.3 Number Plates in Asia

Similarly to Africa, Asia has a wide range of number plate styles with huge variations across different countries including[2]:

Afghanistan: these number plates are black with white Arabic lettering and the country's Emblem displayed on the left hand side of the plate.

China: uses both English and Chinese script to mark the plates, a symbol marks the province of issue followed by a letter and five digits.

India: these plates have a system that uses a LL DD LL DDDD, these signify district codes, unique numbers and optional letters if the numbers have expired.

Indonesia: number plates here are unique as they represent defunct regions of the country, rather than reflecting current conditions, the plates follow a LL DDDD LL pattern.

Japan: has two lines on their number plate, the top one reflecting here the plate was issued and the vehicle class code and the bottom line containing a serial number.

United Arab Emirates: number plates in the UAE follow different formats depending on which emirate you are in. All use both English and Arabic characters and contain up to 5 digits.

Vietnam: follows a DD – DDDDL format which was introduced in 1948 and remains unchanged to this day.

1.5 License plate in Algeria

Algeria plate systems based on a sequential numbering that includes 10 serial numbers, including five main numbers, that represents a special registration of the car series, followed by three numbers, the first number stands for vehicle type (1 passenger car, 2 truck 3 car utilitair, 4 public transport bus, 5 half-engine tractor, 6 peasants tractors, 7 private car traction, 8 vehicle or wounds, 9 degree of locomotive) and the rest two numbers, symbolizing the which year the vehicle put into circulation. It is a feature characterized by Algeria, and the last two digits are symbolic of the state (example, (16) to the capital of Algeria and (01) to Adrar (31) to Oran ,... etc). The following image (figure 1.2) represents a sample of Algerian car plate, the first five serial numbers are placed on the registration of the vehicle on the basis of a numbered series "17737" and placed 1, passenger cars, began operating in 2011, registered 16 in Algiers . In total, we get a special player as follows: 17737 111 16.

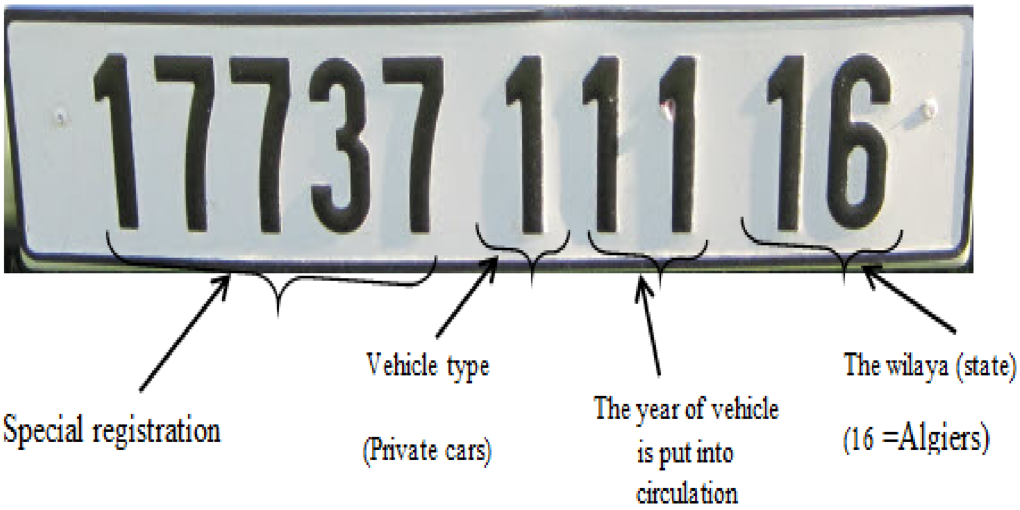


Figure 1.3 The 10 serial numbers of License plate Algeria.

1.5.1 Historic

It should be noted that Algeria has changed after independence in 1962, the automatic numbering system that is similar to that approved in France with the presence of letters, numbers, and the symbol of Algeria Arabic, the letter A, which symbolizes to Algeria with only five digits, then it was in the seventies changes in the numbering of the plate on the back of the new statutes that allowed the adoption of painting existing to date.

(a) (b)

Figure1.4 (On the left) registration plate before 1976, (On the right) registration plate after the 1976[3].

1.5.2 Description of License plate in Algeria

The registration number is reproduced in a manner very similar to the front and the rear of the motor vehicle on a reported pieces attached to the vehicle in ina-movible and separately of the chassis and bodywork. This part called reported license plate must present a reflectorized background whose color varies according to the customs charge regime applied to the vehicle.

The size of the plate approximately 520 mm long and 110 mm wide, and have a white color to the front of the vehicle, while the yellow to the rear, and be rectangular for passenger cars, and for utility vehicles or square plate. should be a reflection of light, which means that it is visible at night, as it should be free of any addition or draw or flag or cosmetically.

Normal series

A vehicle whose owner is resident in Algeria has not submitted an special customs regime, vehicles belonging to companies of mixed economy whose registered office is located in Algeria, the vehicles belonging to a political character associations, vehicles belonging the institutions of state and government, vehicles belonging to wilayas, municipalities and public institutions.

Colour:

- Front plate: Figures black Arabic backgrounds reflectorize gray white.
- Rear plate: Figures black Arabic backgrounds reflectorize yellow.
- Dialling: black.

Figure 1.5 Current passenger series, front plate in black on white (On the left).rear plate in black on yellow (On the right).

The Special Series

Vehicles circulating temporarily free of duty or are subject to special rules dc circulation.

Free import:

Vehicular the diplomatic and consular corps (CMD - CD - CC) benefiting from duty-free.

COLOR: The identification is reproduced on the back plate and the front plate on reflectorize a green background with letters in Latin characters and digit black Arabic.

The registration of vehicles of diplomatic and consular corps is the competence of the Minister of Foreign Affairs.

Figure 1.6 Diplomatic series in black on green. The Registration consists of the letters CMD, Followed by two numerals and one numeral.

The letters CMD are used for the Ambassador. The first two numerals denote the embassy Where stands for EU 97.

Temporary Importation (IT)

The vehicles belonging to diplomatic agents, consular or similar residing in Algeria. The registration number is composed of four groups of Arabic numerals separated by an apparent indent:

- A diagram identifying the wilaya of the vehicle is registered,

- The code of the Embassy or international origin whom or to which is attached the vehicle registered.

Figure 1.7 Diplomatic series, front plate in black on white.

The Registration Consists of four numerals, Followed By 66, three numerals Reviews and another two numerals.66 stands for Diplomatic corps, 004 stands for 2004 and 23 Denotes the state (wilaya) Annaba. To the left of the plate is a blue band with the DZ oval in white above-the white twelve European stars.[4]

1.6 Conclusion

In this chapter we presented in general way, historical and definition of registration plate, the registration plate in Europe, Asia and Africa, and the license plate in Algeria.

In the next chapter, we will describe the different phases of Automatic Number plate recognition system (ANPR).

Chapitre 2

Automatic license plate recognition (ANPR) system

2.1 Introduction

Automatic Number plate recognition (ANPR) system is a technology that finds its essence in the last 20 years in the development of image processing technologies as well as in OCR (optical character recognition).

The license plate recognition system applies generally image processing and character recognition technology in order to identify vehicles by automatically reading their license plates.

This robust and efficient system becomes more and more a necessity in managing multiple domains such as traffic and road safety, parking management, the pursuit of criminals. In this chapter, first we present the license plate recognition system, different stages of this system and introduce different methods for each stage, finally we saw some work on the subject

2.2 Historique

In 1967, the Automatic Number Plate Recognition (ANPR) was developed. Three years later the first prototypes of the developed system were tested in England. The inceptive use of the ANPR was in the 1980s. The technology was used covertly and was very expensive.

Since then license plate recognition has progressed and been used by police and other organizations for different purposes and has become cheaper and faster, but not cheap enough for private use[4].

2.3 Difficulties in the recognition of license plate

The variations in Number plate types and environments create challenges in Number plate recognition. These can be like that Number Plate Variations can be one of the given below:

1. Location of Plate: - Number Plate Exist or Not. Having more than one number plate, Different location of Number plate.

2. Size of Plate:-There can the size of plate can be varying due to capturing of image.

3. Plate Colour: - Different Plate having different Colour variations in background or also based on capturing device.

4. Character & Number Font: Number Plates of different Countries may Contains the data in different format than others.

5. Occlusion Plate: Plates may be covered by dust or it can be blurred type.

6. Other: where the Number Plate Can Be tilled, a plate having frames and screws etc.

7. Different Illumination: Our taken images may have different types of illumination, Can be due to weather condition, due to environmental condition or due to vehicle own or other lightning etc.

8. Image Background: The image background can contains complex figure, the area of plate same as background etc.

2.4 Description of Automatic Number Plate Recognition system (ANPR)

Generally, license plate recognition system includes the following steps: vehicle image acquisition, vehicle image Pre-Processing, Extraction License Plate, license plate Pre-Processing, Character Segmentation, and Character Recognition. The detection step is crucial for the LPR result. Some application use two sets of LP (license plate) and non LP regions for LP classification.

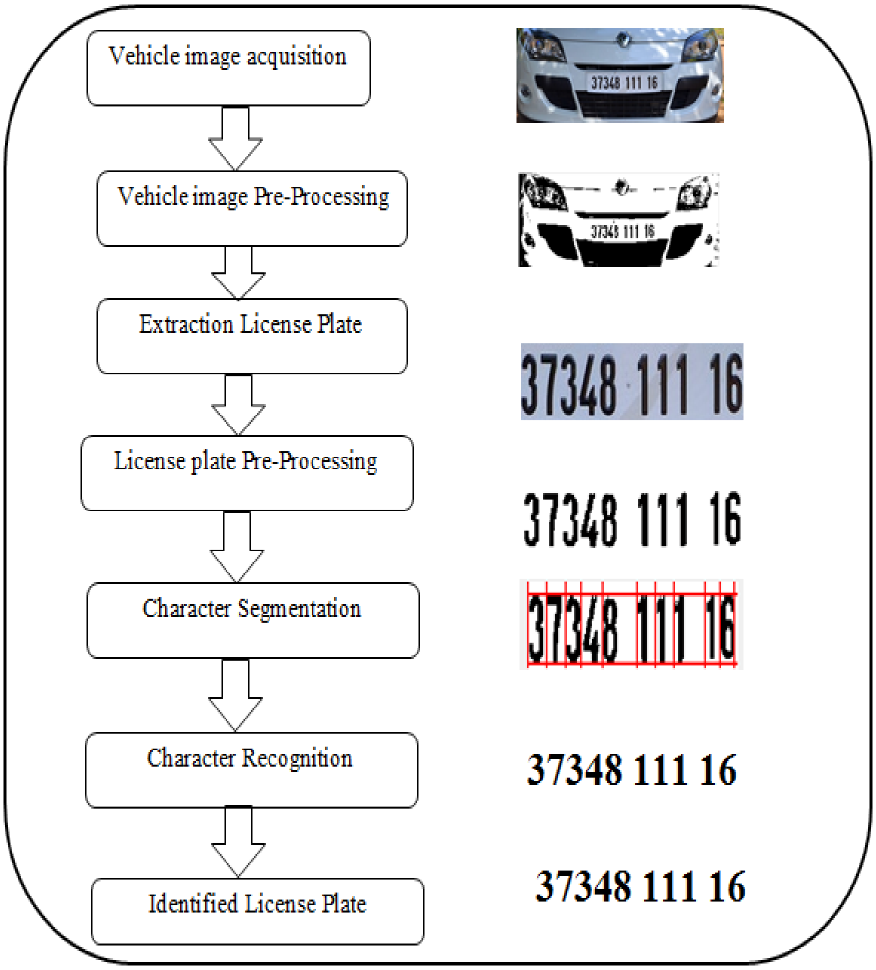


Figure2.1 Steps of ANPR System.

2.4.1 Image Acquisition

Initial Phase for Number Plate Recognition is Image acquire can be from any method like image analog or digital, where the image can be obtained from any video. Image acquisition is very important step in the number plate recognition, as it is affected by illumination, weather, angle of rotation, resolution of image required etc.

Where the Image obtained from any Source can be in any image format like jpeg., Gif, ,tiff.

Figure2.2 Steps of ANPR System.

2.4.2 Vehicle image Pre-Processing

This step is essential to enhance the input image and making it more suitable for the next processing steps. Several pre-processing algorithms for ANPR systems are discussed below.

Grayscaling Process

Image obtain from any storage can be of any color, any format or different properties. Here the main second step is Vehicle image pre-processing in which the original or RGB image is converted to Gray Scale Figure 2.3.

Figure 2.3 Grays Cal Image.

Binarization Process

In [5] Otsu binarization method is used for preprocess the image. The acquired image is segmented into several sub-regions.

For each sub-region, threshold value is calculated. According to Anagnostopoulos et.al.[6] pre-processing is performed to detect the Region of Interest (ROI) even in the ambient illumination conditions.

It is done using image masking, binarization with Sauvola method. In Sauvola method, locally adaptive thresholding is used to convert a gray scale image to a binary image.

The value of threshold mainly depends on the local statistics like range, variance and surface fitting parameters. In the case of badly illuminated areas, calculated threshold value will be low.

Figure 2.4 Binary Image Using Otsu's Method.

Median filtering or noise reduction

Median filter is used for eliminating the unwanted noisy regions. In this filtering method, the 3×3 matrices is passed around the image.

The dimension of these matrices can be adjusted according to the noise level. The process of working is

- One pixel is chosen as centre pixel of the 3×3 matrices,
- The surrounding pixels are assigned as neighbourhood pixels,

- The sorting process are employed between these nine pixels from smaller to the bigger,
- The fifth element is assigned as median element,

these procedures are implemented to the all pixels in plate image.

2.4.3 Extraction License Plate

Number plate detection is the key step of vehicle identification system. It affects the result of whole system. The goal of this phase, given a frame captured from input video is to produce the region with high probability of containing the number plate area.

Most of the number plate detection algorithms fall in more than one category based on different techniques. To detect vehicle number plate following factors should be considered:

1. Plate size: a plate can be of different size in a vehicle image.
2. Plate location: a plate can be located anywhere in the vehicle.
3. Plate background: A plate can have different background colors based on vehicle type. For example a government vehicle number plate might have different background than other public vehicles.
4. Screw: A plate may have screw and that could be considered as a character.

In this stage, the location of the license plate is identified and the output of this stage will be a sub-image that contains only the license plate. This is done in two main steps.

- Locating a large bounding rectangle over the license plate.
- Determining the exact location of the license plate.

In the following sections common number plate extraction methods are explained.

Edge detection

Edge detection is fundamental method for feature detection or feature extraction. In general case the result of applying edge detection of algorithm is an object boundary with connected curves. It becomes very difficult to apply this method to complex images as it might result with object boundary with not connected curves. Different edge detection algorithm / operators such as Canny, Canny-Deriche, Differential, Sobel, Prewitt and Roberts Cross are used for edge detection.

Figure 2.5 edge Sobel Image.

vertical edge detection method is utilized for locating the LP(license plate). So Robert's edge detector is used to emphasize the vertical edges.

There will be many abrupt intensity changes but a cluster of $10 - 15$ sharp intensity changes is considered as plate zone. Image is convolved with horizontally oriented rank-filter of $M \times N$ pixels.

This leads to a bright-elongated spot of ellipsoidal shape in the plate's area. The last step is horizontal projection. Figure2.6 illustrates the License Plate Detection LPD used in [7].

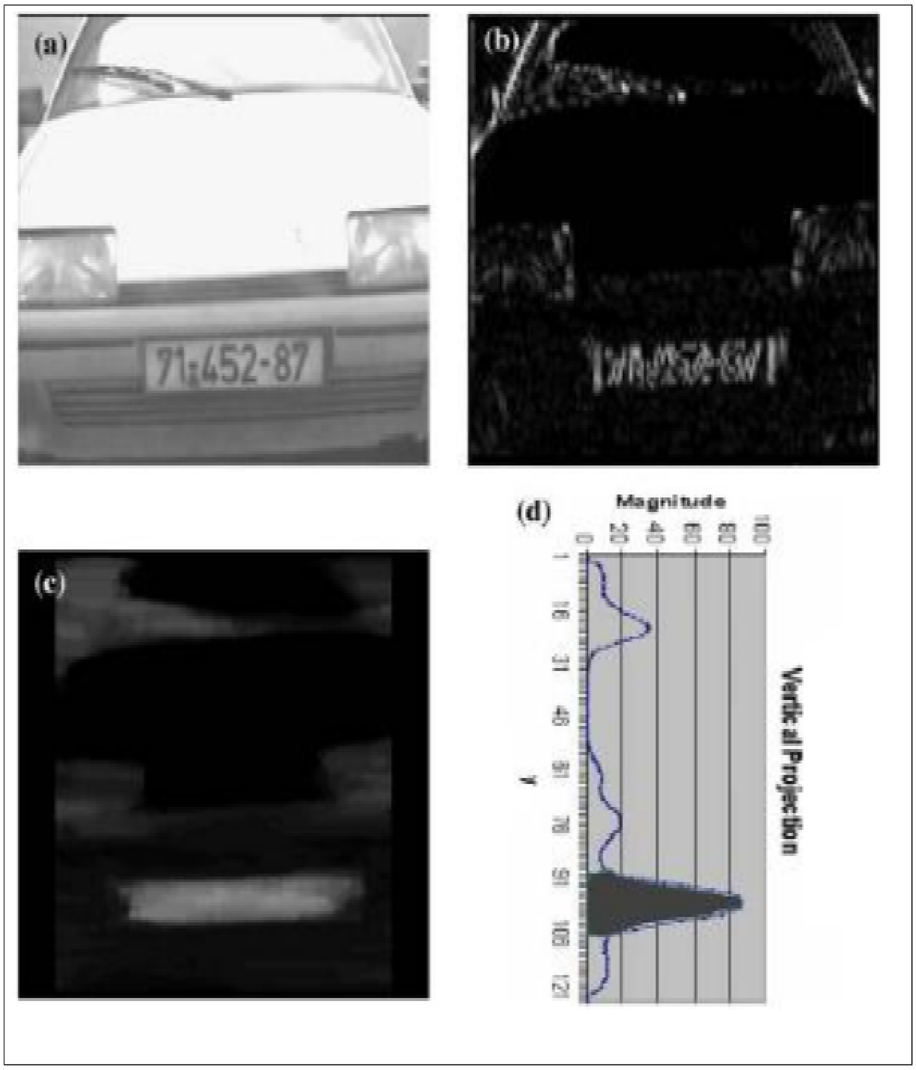


Figure 2.6 (a) Original Image (b) Vertical Edge Map (c) Rank Filtered Image (d) Vertical Projection [7].

Morphological Operation

The main objective of this step is to find out the rough location of number plate. It looks for objects having specific size and aspect for each connected component in the image.

Here two algorithms called Erosion and Dilation [9] are used. The order between these algorithms is very important since the reverse process would give a completely different result [8].

The output of this step is to find all the possible location of number plate area in image.

Connected Component Analysis

CCA or blob extraction is used to find the exact location of number plate. The number plate of car has certain properties which can be used to detect the number plate.

Properties such as aspect ratio, width of number plate and total number of pixels present in the number plate can be used to extract the number plate area[8].

Hence all the regions that do not satisfy this property can be rejected and we get the exact number plate location.

This number plate location can be further used for character segmentation and character recognition to identify the car.

Blob detection

Blob detection is used to detect points or regions that differ in brightness or color as compared to surroundings.

The main purpose of using this approach is to find complimentary regions which are not detected by edge detection or corner detection algorithms.

Some common blob detectors are Laplacian of Gaussian (LoG), Difference of Gaussians (DoG), Determinant of Hessian (DoH), maximally stable extremal regions and Principle curvature based region detector.

Hough Transform

It is a feature extraction technique initially used for line detection. Later on it has been extended to find position of arbitrary shape like circle or oval. The original algorithm was generalized by D.H. Ballard [10]

fuzzy logic

In [11], fuzzy logic is used to locate LP. The author framed some rules to explain about the LP and gave some membership functions for fuzzy sets - bright, dark, bright and dark sequence, texture and yellowness to obtain the horizontal and vertical plate positions. But this need is very sensitive to the LP color and brightness.

It also takes longer processing time compared to conventional color based methods.

sliding concentric window (SCW)

In [12], for faster detection of region of interest (ROI) a technique called sliding concentric window (SCW) is developed.

It is a two-step method contains two concentric windows moving from upper left corner of the image. Then statistical measurements in both windows were calculated based on the segmentation rule which says that if the ratio of the mean or median in the two windows exceeds a threshold, which is set by the, then the central pixel of the windows is considered to belong to an ROI.

The two windows stop sliding after the whole image is scanned. The threshold value can be decided based on trial and error basis.

2.4.4 License plate Pre-Processing

Thresholding

Thresholding is one of the simplest and most popular method in image segmentation. Two common types of thresholding are outlined as follow[16]:

- Local thresholding is referred when an image is partitioned into subregions, and each subregion carry different value of threshold. Local threshold method also called as adaptive thresholding schemes
- Global thresholding is referring to assigning only one threshold value to the entire image.

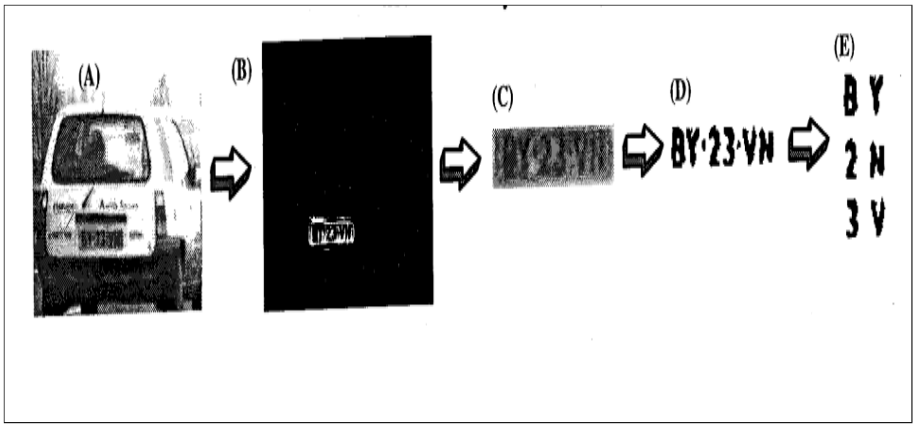


Figure 2.7 The various stages in the segmentation process. (D) the license plate after global thresholding[13].

Thresholding techniques also can be categorized into two levels:

- Bilevel thresholding: the image is two (2) regions which are object (black) and background (white).
- Multithresholding: the image is composed of few objects with different surface characteristics thus need multiple value of threshold.

Thresholding also can be analyzed as classification problem, such that classifiying bilevel segmentation of an image into object and background. Among the most common methods found for thresholding in image segmentation are listed as the following:

- maximum entropy method
- Otsu's method (maximum variance)
- . . . etc.

Edge detection

Edge detection techniques have been used as the base of another segmentation technique. Basically, edge detection is also an independent process in image processing.

Edge detection, or sometimes it is called as edge finding is also closely related to region detection.

We need to find the region boundaries first before we can proceed to segment an object from an image.

This is because the edges identified by edge detection are frequently disconnected. It means that we have to find the boundaries in order to get the edges.

In segmentation, line detection is done to divide regions into meaningful information. One of line detection technique is Hough transform.

Hough transform is designed specifically to detect lines. A line is a collection of edge points (that are adjacent and have the same direction). The Hough algorithm will take a collection of few edge points.[14]

Histogram-based methods

Histogram-based method is one of the frequently used for image segmentation techniques. In this method, we will produce a vertical and a horizontal histogram accordingly. This process is to get a group of pixels in vertical and horizontal regions where they will lead to distinguishing the gray levels of the image.

In common, an image will have two regions: background and object. Normally, the background is assigned as one gray level whiles the object (or also called as subject) is another gray level. Usually, background will secure the largest part of the image so the gray level of it will have larger peak in the histogram compared to the object of the image.[15]

Region-growing methods

Region Growing and Shrinking [15] technique use row and column (r , c) based image domain. It can be considered as subset of clustering methods, but limited to spatial domain. The methods can be:

- Local : operating on small neighbourhoods, or
- Global : operating on the entire image, or
- Combination of both

Split-and-merge methods

There is an alternative for segmentation method called split and merge [15]. Split and merge is also called as quadtree segmentation where it based on quadtree partition. The data structure used in split and merge is called quadtree where a tree which has nodes and each node can have four children. It divides regions that do not pass a homogeneity test, and combines regions that pass the homogeneity test.

For this, we propose the following algorithm, where the pseudo-code can be simplified as the following:

- To get width of y-axis of the image to divide into sub region
- To get width of y-axis of the image to divide into sub region
- To divide into sub region

•To remove blank space

•To get same size after region has been divided

2.4.5 Character Segmentation

After locating the LP and skew correction, next step is the segmentation of characters. Character segmentation is the procedure of extracting the characters from the LP image.

To get individual character and number image by using, vertical and horizontal scanning method.

Vertical Scanning: Vertical scanning technique is used to dig out each character from the image found on one st and last column part.

It's into the image by part vertically from [0,0] until [width, height] that is dead in columns by column scanning. as a result of the input image can be a binary image that comprises one and 0 values, vertical scanning theme is simple to be dead.

The scale between each first and last column area unit about to be computed. At last, every character or varieties area unit about to be slice to separate it from the plate background.

Every component goes to be kept in array individually for next horizontal scanning method.

Horizontal Scanning: One each component is saved individually in preceding step, horizontal scanning will verify the first and last rows of the image. The intention is to eradicate additional higher and lower region from the image.

To conclude, the tip results of this technique area unit about to be an image with filler with character or vary elements with none spare areas. The segmented characters are shown in Figure 2.8.

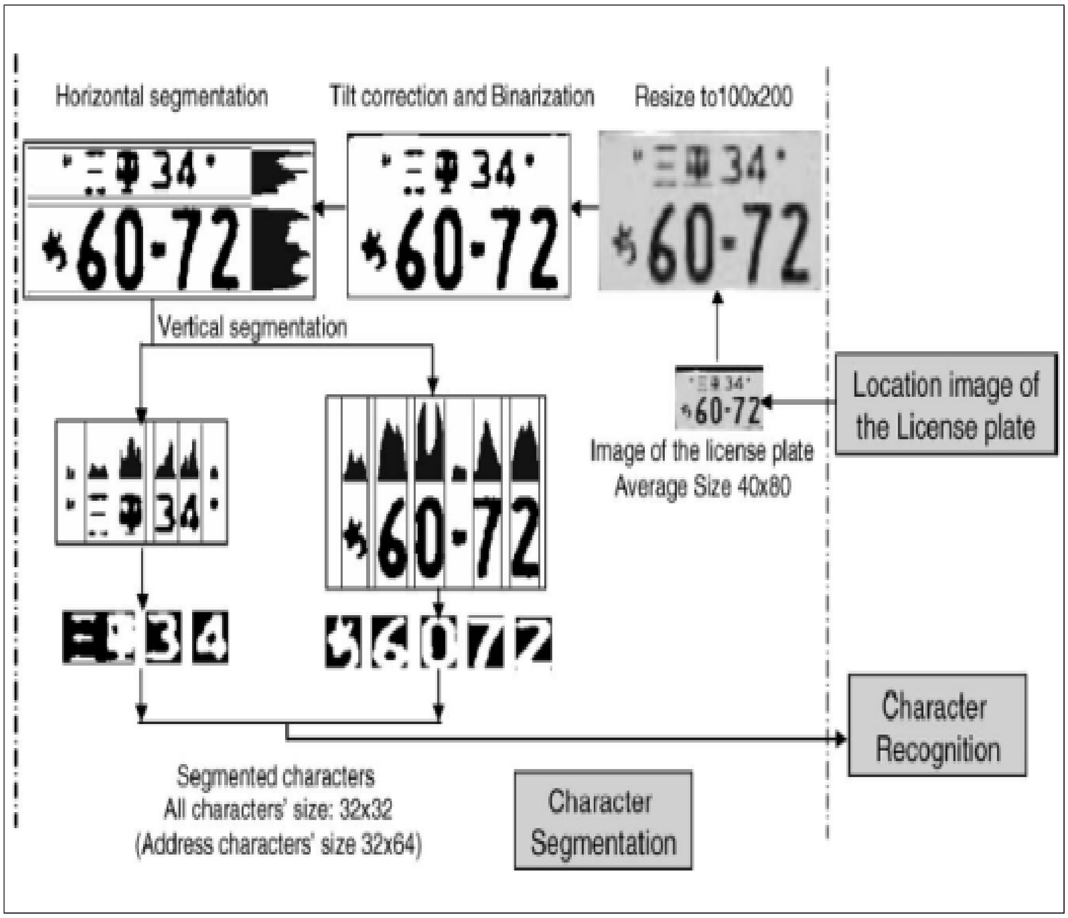


Figure 2.8 Flow chart of character segmentation [16]

To wrap up, a good segmentation process should turn out uniform and homogeneous regions with respect to some characteristics such as gray tone or texture as well as simple regions without many small holes. The output from the segmentation will be used in the next stage which is character recognition.

2.4.6 Character Recognition

After segmenting the characters, the next step is character recognition. There are several methods have been proposed for character recognition.

The last stage of an ALPR system is the character recognition stage. Different types of neural networks, such as Hidden Markov Model (HMM), Support Vector Machine (SVM), and Artificial Neural Network (ANN) are mainly used to classify the characters. Other than neural networks, pattern or template matching techniques are also used to recognize the characters. Some of them are discussed below.

Support Vector Machine

A support vector machine (SVM) is a type of supervised learning methods that analyse data and recognize patterns. The SVM is used for classification and regression analysis. Support Vector Machine (SVM) was used to recognize the characters in Korean license plates. They used four SVM base character recognizer in their system to recognize the characters and digits in four different parts of the license plate, such as upper character, upper numbers, lower character, and lower numbers.

The vectors media machines also called maximum margin classification are supervised learning techniques based on the theory of statistical or machine learning. SVM are relatively new, they appeared in 1995 following the work of Vapnik. SVM deals with a classification problem by classes.

The general principle of classification by SVM can be explained by the following figure:

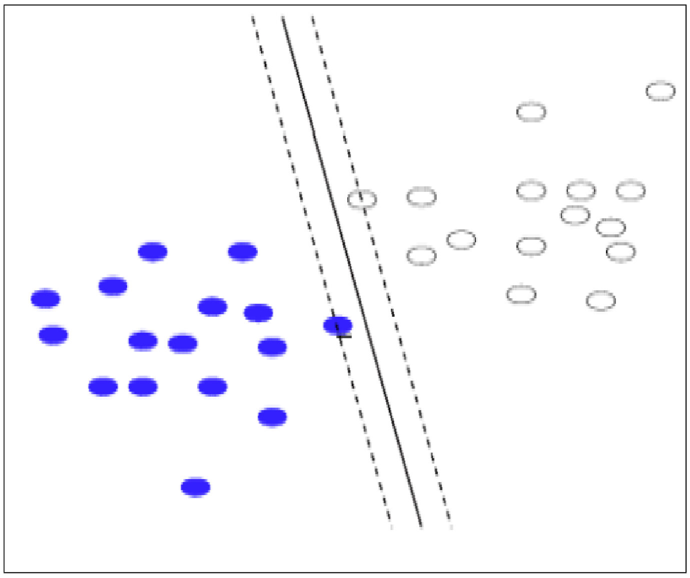


Figure2.9 Principle of SVM

The goal of SVM is to determine whether an item belongs to a class or not. We have a set of data and we try to separate the data into two groups. The first is the set of data belonging to a class, these data are labeled by $(+)$ and another set that contains the elements that do not belong to the class so labeled $(-)$. The SVM algorithm to find a separating hyperplane between the two groups. To optimize the separation SVM seeks the hyperplane for which the distance between the border of the two groups and the nearest points is maximum, it is the principle of maximizing the margin.

Neural Networks

A neural network is an artificial calculation model from biological models. This model simulates the behavior of the human brain. Neural networks are characterized by their ability to learn. In general, the structure of a neural network is composed of a succession of hidden layers. The input layer is connected to the output layer of the network through the hidden layers according to a defined or architecture, such as architecture of the perceptron, the multilayer perceptron. Each hidden layer consists of a number of neurons connected to the previous layer. The next layer receives as input the outputs of the previous layer of the power system. The input vector for each layer is weighted by a poids. A using an activation function, the network shall calculate its weight in order to produce an output

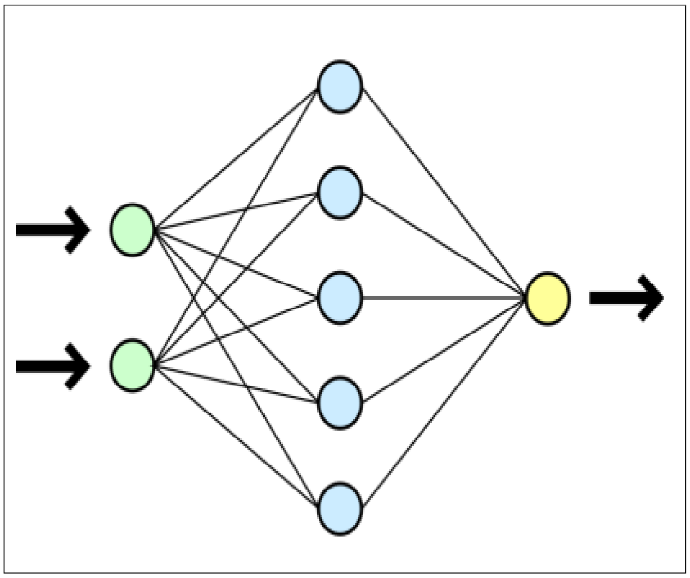


Figure2.10 Example of a neural network

Template matching

Template matching is one of the Character Recognition techniques. It is the process of finding the location of a sub-image called a template, inside an image.Template matching involves determining similarities between a given template and windows of the same size in an image and identifying the window that produces the highest similarity measure. It works by pixel-by-pixel comparison of the image and the template for each possible displacement of the template. This process involves the use of a database of characters or templates. There exists a template for all possible input characters. Templates are created for each of the alphanumeric characters (from A-Z and 0-9) using 'Regular' font style. Figure2.11 shows the templates for few of the alphanumeric characters.

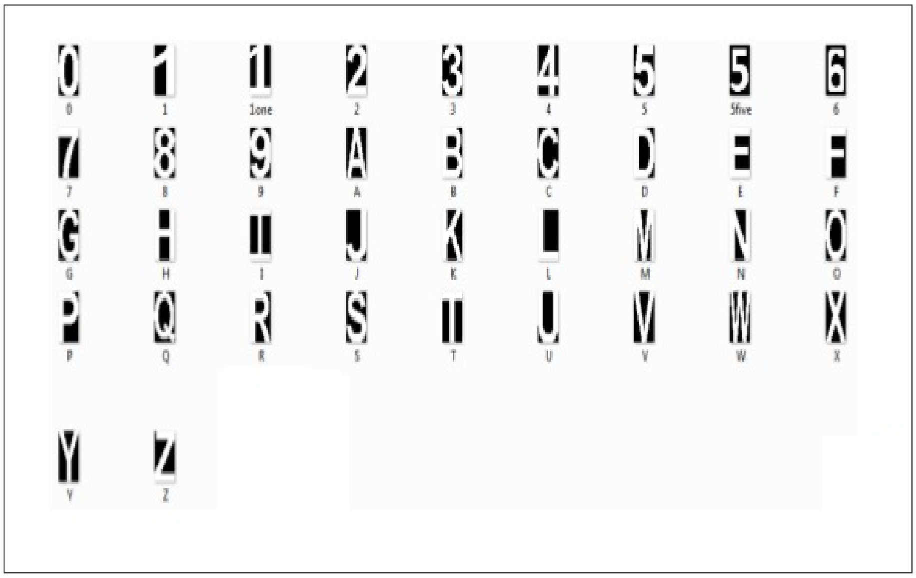


Figure 2.11 the Template of characters.

2.4.7 Identified License Plate

From the description in the character treaty parameters, the recognition module searches among the reference models involved those closest to him. After calculating the output, one must extract maximum values, the line corresponding to this value represents a sequence of numbers if those numbers are obtained equal to the sequence of numbers from the picture then entering the license plate is recognized else is rejection.

2.5 Literature Review

In the literature Review many Number Plate Recognition methods have been purposed. Where the number plate recognition is the hotspot area of research now a days due to rapid development of transportation systems and from literature review we can see various existing techniques take place for number plate recognition.

S. Chang, L. Chen and al, In 2004, this paper, Number plate recognition method here first used Colour Edge Detection and fuzzy maps then steps taken into account were (1) Pre-processing:- Consists binarization using variable thresholding technique then Connected Component algorithm was applied to binarized plate to eliminate undesired area. Huge transformed was taken into account for alignment of extracted components for further process.(2) OCR (Optical Character Recognition) here the character recognition process takes and task of character categorization accomplished by the compositional semantics of license numbers, Topological Shorting to compute the topological features of characters for further process. Then self-Organizing Template test was performed to match the input character to the database and best match was find. Experiment was performed on 1601 images and the success rate achieved approximate 95.6% and overall success rate take place up to 93.7% [17].

Christos Nikolaos and E. Anagnostopoulos, In 2006 the method mainly consists the tasks (1) License Plate Segmentation: - binarization with Sauvola Method and use the Sliding Concentric Windows (SCWs) segmentation technique for faster detection of region of interest (ROI). (2) License Plate Processing: - Image was transformed into standard size by bicubic interpolation method. (3) Character Recognition:-Trainable OCR (Optical Character Recognition) System based on Neural Networks was taken into account which used the approach of PNN (Probabilistic Neural Network) with two individual probabilistic networks one for the alphabet and other for the number recognition. The Experiment was performed on 1334 images and the segmentation rate was achieved around 96.5% and With the PNN approach plate recognition recorded 89.1%.Oveall rate of success achieved was 86.0% while the success rate from 90-95% also was reported by restricting some condition like distance of plate captured, angle of plate viewed, illumination conditions and low background complexity[18].

SerkanOzbay and Ergun Ercelebi, In 2007 the system mainly accomplice with three major steps (1) Plate Region Extraction: - Image Captured to binary image and then Edge detection technique, smearing algorithms were used for extracting the Region of Interest (ROI). A morphological operation was performed for the dilation of Image (2). Segmentation of characters: - Character segmentation was provided by smearing algorithms, Morphological Operations and some filtering process. (3) Recognition of Characters: - Statistical based template matching provide the best match of segmented character which taken as input. And the accuracy for different step here for Plate Region Extraction tested on 332/340 achieved 97.6% for Segmentation of character over 327/340 images achieved 96.0% and for Recognition of Characters over 336/340 was achieved 98.8% [19].

C. Nikolas and E. Anagnostopoulos, In 2008 this paper mainly aims to present the various existing techniques to categorize and assess them in general the number plate recognition consist three steps (1) Extraction of a ROI: - edge statistics, morphology, Connected component analysis (CCA). (2) Segmentation of the plate characters: - Using Histogram Processing, Mathematical Morphology, Local/Adaptive Thresholding and Transformations. (3)Character recognition:- Using Statistical/Hybrid Classifiers, Pattern or Template Matching. Better Results have been achieved by using the concept of neural networks and statistical classifier approach but a large amount of learning training sample needed for the better work [20].

C. Nelson KennadyBabu and al, In 2010 the algorithm for number plate recognition composed with number of following steps (1) Pre-processing and Plate Recognition: - To improve the image Quality colour image was converted to gray level image using Standard NTSC model then median filtering was applied for noise reduction. Feature-based number plate localization method was implemented for further process. (2) Character Segmentation: - Otsu method for threshold the plate values. (3) Character Recognition: Statistical feature extraction has been implemented for the character recognition process. Performance analyzed for different part of purposed method was 85% for number plate localization, for character segmentation 95% and for character recognition it's was 82%. [21]

H.E. Kocera and K. K. Cevikb, In 2011 the approach mainly based on Artificial Neural network while the steps proposed was (1) Plate Localization: - Canny Edge Detector used for the image localization purpose. (2) Character segmentation: - Histogram approach was taken into account for Contrast extension while median filtering for noise reduction (3). Feature Extraction: - Artificial Neural Network (ANN) was proposed in this process. Two separate ANN used one for Character and other for character extraction because confusion was high when combined approach was applied to both character and numbers so to increase the success rate separate ANN was implemented. (4)Character Recognition: - Multi layered perceptron (MLP) model of ANN was used for the character recognition purpose. Test was taken on 259 vehicle images and out of which 247 was recognized and overall accuracy was achieved near about 95.36% [22].

Ying Wen and Yue Lu ,In 2011 Algorithm for number plate verification mainly accomplice four steps (1). Licence Plate Location: - Local Otsu and Improved Bernsen Algorithm was implemented (2). Licence Plate Detection: - Connected Component Analysis (CCA) based on Pixel Connectivity (3). Character Segmentation: - Horizontal and Vertical Correlation approach was taken into account for segmentation of characters. (4). Character Recognition: - Feature Extraction for character Recognition, feature extraction for number recognition has been implemented using Elastic Mesh approach which use the concept of Support Vector Machine(SVM). Experiment was tested on no's of images and accuracy rate 97.16% for locating the plate, 98.34% for segmenting the characters, 97.88% recognizing the characters achieve, and 93.54% Overall recorded [23].

S. Kranthi and al, In 2011 Automatic Number Plate Recognition system mainly use the techniques of Edge finding method and Window filtering method. Where the localization of Plate consists the step of converting the Original Colures image to the gray level image. Identification of no. plate horizontally take place in which row represents the peak value of the region and then high change region was selected and vertical approach was applied. Then combined region was selected for the further process. While Edge finding method provides the complex region with high intensity value so window size can be fixed for finding the good result. OCR (Optical Character Recognition) provide the methods of Template Matching and character segmentation [24].

Rupali Kate, In 2012 Number plate recognition system was composed of mainly these steps (1) Pre-processing:- Image converted to gray scale from Original was goes for further process and median filtering was applied for noise removal (2) Plate Localization: - Morphological Operations were performed for Number plate localization (3) Character Segmentation: - the process of character segmentation take place using regionprops functions which take place into MATLAB. (4) Character Recognition: - Where the character recognition task was performed by the functions of MATLAB using OCR (Optical Character Recognition) Approach. Template matching process take place and the best match value to the input to the database was founded as a result [25].

C. Chunyu and al , In 2013 vehicle license plate recognition System was per posed which contains mainly four steps (1). Pre-processing and Edge Extraction: - firstly the simple pre-processing of image take place and then edge extraction without filtering takes place. (2). Licence Plate Localization: - Use the Micron position technology and edge image was calculated by horizontal and vertical direction. (3)Character Segmentation: - Vertical area Projection Method was implemented for the character segmentation approach. (4). Character Recognition: - Character recognition process step implement the Artificial Neural Network approach and then at last Template matching algorithm was taken into account and best matched value was returned as a result[[26].

Shan Du, In 2013 Paper presents the review of various existing technology which have been used in different phase of Number plate recognition. Mainly used three phase of number plate recognition system use techniques (1) License Plate Extraction techniques: - Using Boundary/Edge Information, Global Image Information, Texture Features, Color Features (2). License Plate Segmentation techniques: - Using Pixel Connectivity, Character Contours, Profiles of Projection, and Characters Prior Knowledge (3). Character Recognition techniques: - Using Raw Data, Extracted Features. Paper provide the Pros/Cons of various technology used at various step of Number plate recognition process [27].

J. K. Chang and al, In 2013 real time vehicle plate recognition was implemented mainly in two steps which can be further divided (1). Plate Location Detection:-this paper presents the implementation view of Vertical edge techniques and then detected lines were binarized. Verification of Upper number plate area was taken into account, Horizontal border, Excluding of border lines (2). Licence Plate Recognition: - Histogram technique was implemented for localization of plate and then character recognition take place by Normal factor (NF) Calculation. RLPR Test was taken on 250 images and out of which 231 images exact was recognized with accuracy rate 92.4% 17 were unrecognised and 2 were misrecognised [28].

Wei Xie and Y. Wu, In 2014 License Plate Automatic Recognition System was developed which consists six steps (1) Image Acquisition: - Image was taken from Digital or anlog Camera for further process. (2) Image Pre-processing:- Edge Detection Technique used for the image processing purpose then (3). License Plate Locating: - Mathematical Morphology techniques use for the licence plate localization which use the concept of shape, size etc. features of image not work on numeric type values. (4). Character Segmentation: -Vertical and Horizontal approach was consider for Character Segmentation (5). Character Recognition: - The further process of character recognition was take place with the help of Neural Network All the proposed work was implemented on GUI interface with the help of MATLAB. [29]

H. Kaur and N. Kumar Garg, In 2014 Vehicle Plate licence recognition mainly used here two approach Neural Network and k- means and consists the various steps (1). Input Image to gray scale image with thw help of MATLAB (2) Dilation performed for improving theimage structure (3).Horizontal and Vertical Histogram technique for Localization of Image (4). Low pass filtering to Histogram to smoothing out (5).Histogram technique provides the region having the more probability of finding number (6) Region of Interest (ROI):-Neural Networks and k-means approach was taken into account. Using k-means accuracy achieved was 86. 23% and using Neural Network it was approximate 96.5%. [30].

P.Prabhakar and P.Anupama, In 2014 Vehicle License Plate Detection and Recognition System here composed of four major steps (1) Preprocessing:- where the original or RGB image is converted to Gray Scale image using NTSC Standard method. (2).Localization:- Morphological Operation were performed and huge transformation was taken into account for edge detection Process. (3). Segmentation: - Horizontal Projection was applied for segmentation process. (4). Recognition: - Template matching process take place in which the pixel values of the matrix of segmented character and the template matrix were compared and best match value was returned as output [31].

2.6 Conclusion

In this chapter various Number Plate Recognition techniques has been discussed in details which were used by many researcher. The Number Plate Recognition (NPR) System mainly contains the three major steps of Region of Interest Extraction, Number Plate Extraction, and Character Recognition using number of different techniques which are disused in paper clearly. Number plate recognition is challenging in case of different weather conditions and differ number plate formats. There are number of NPR techniques purposed in previous years.

Chapitre 3

Support vector machine(SVM)

3.1 Introduction

In this chapter, supervised automatic classification technique is detailed. This technique, based on the structural risk minimization, has proven its performance in several areas.

Support vector machine (SVM) are a set of techniques of training intended to solve problems of discrimination,i.e. to decide with which class a sample belongs, or of regression,i.e. to predict the digital value of a variable, SVM is a classification method particularly well suited for treating high dimension data.

3.2 Idea of the SVM

The main idea of the SVM is to project the data into a space of larger dimension called feature space, so that non-linearly separable data in the input space become linearly separable in the space of features. Applying this in the space for construction of an optimal hyperplan separating two classes, one obtains a classification function which depends on a scalar product of the image data of the input space in the feature space.

This scalar product can be expressed under certain conditions, for the functions defined in the input space, called nuclei.

This multiple choice of SVM kernel is more interesting and richer especially since one can always seek new nuclei that may be better suited to the task you want to accomplish. The three most used kernels are: the linear kernel, polynomial kernel and Gaussian kernel also noted RBF (Radial Basis Function).

3.3 History

Separators large margins based on two key ideas:

▷ the concept of maximum margin .

▷ the concept of kernel function.

Both concepts existed for several years before they are pooled to build the SVM.

- The idea of hyperplans maximum margin has been explored since 1963 by Vladimir Vapnik and A. Lerner, and in 1973 by Richard Duda and Peter Hart in their book Pattern Classification.

The theoretical foundations of SVM were explored by Vapnik and his colleagues in the 70s with the development of the theory of Vapnik-Chervonenkis .

- The idea of core functions is not new: the Mercer theorem in 1909, and usefulness of kernel functions in the context of machine learning was shown in 1964 by Aizermann, Bravermann and Rozoener.

But it was not until 1992 that these ideas will be understood and collected by Boser, Guyon and Vapnik in an article, which is the founding article of large-margin separators.

The idea of variable springs, which solves some important practical limitations, shall be introduced in 1995.

From that date, which corresponds to the book's publication Vapnik, SVM are gaining popularity and are used in many applications.

3.4 Principle of overall functioning

For two classes of examples given, the goal of SVM is finding a classifier that will separate the data and maximize the distance between these two classes. With SVM, this classifier is a linear classifier called hyperplan.

3.4.1 Basic knowledge

Hyperplan

In the case of a binary classification, separating hyperplan is called a hyperplan that separates two classes (Figure 3.1); in particular it separates their learning points. Since it is usually not possible to find one, so we will simply look for a discriminating hyperplan which is an approximation in the sense of a criterion to fix (maximize the distance between these two classes) [32]..

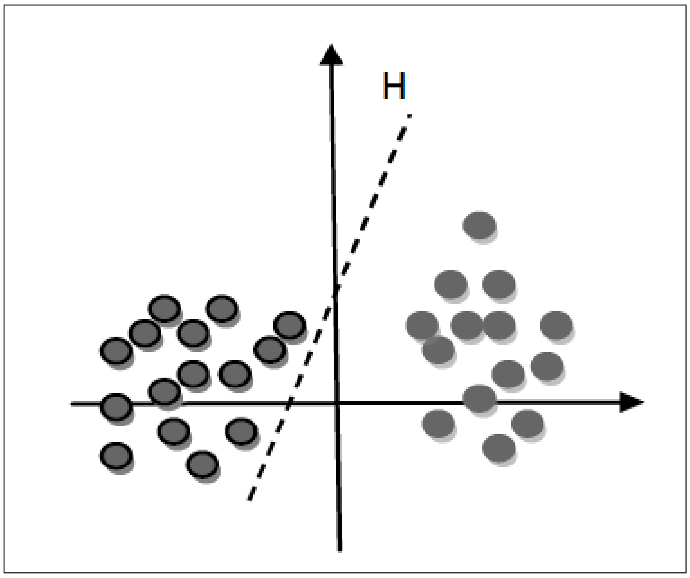


Figure3.1 The hyperplan H that separates the two sets of points.

Vectors supports

For a separable hyperplan for determining the task of SVM is to use only the nearest points (i.e. points on the border between the two classes of data) from the total set of learning, these points are called vectors supports *Fig 3.2* .

Margin

There are endless hyperplan able to perfectly separate the two classes of examples.

The principle of SVM is to choose one that will maximize the minimum distance between the hyperplan and learning examples (i.e. the distance between the hyperplan and the support vectors), this distance is called the margin. [32].

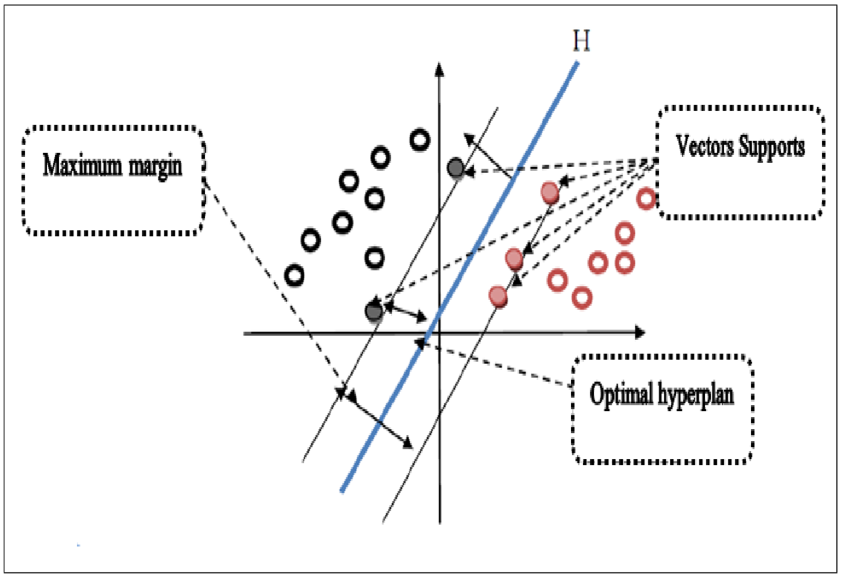


Figure 3.2 the optimal hyperplan H, and support vector maximum margin

3.4.2 Basic properties

maximum margin

Intuitively, having a wider margin provides more security when a new class instance.

In addition, if there is the classifier that performs best vis-a-vis the training data, it is clear that it will also be one that will best classify new examples.

In the diagram *Figure 3.3*, the right part shows that with optimal hyperplan, another example remains classified so that it falls in the margin.

It is found on the left side with a smaller margin, the example is seen misclassified.[32].

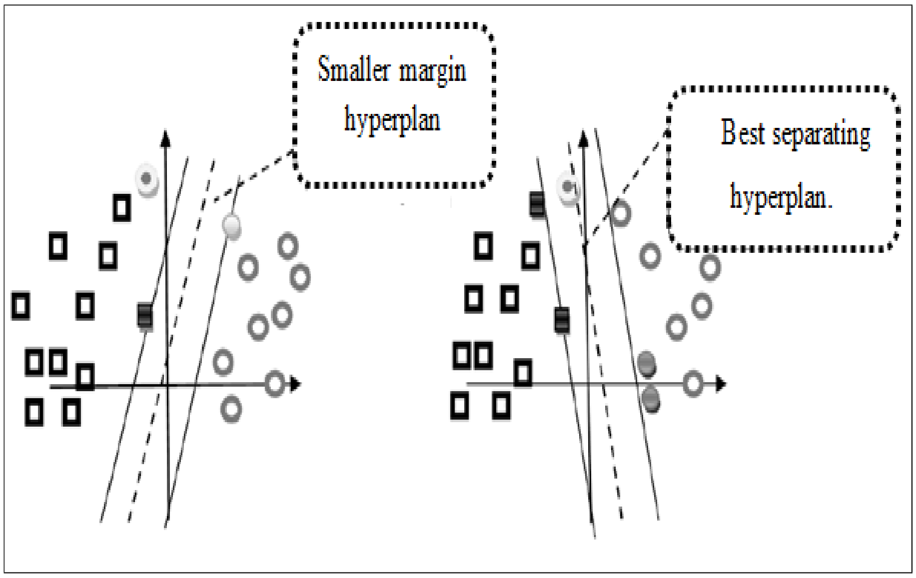


Figure 3.3 Best separating hyperplan.

Linearity et non-linearity :

Among the models of SVM, there is the case linearly separable and non-linearly separable case.

The first are the simplest of SVM because they can easily find the linear classifier. In most real problems there can be no separation between the linear data, the maximum margin classifier can not be used because it only works if the training data classes are linearly separable. [32].

To overcome the disadvantages of non-linearly separable case, the idea of SVM is to change the data space.

The non-linear transformation of data can allow a linear separation in a sample new space.

So we will have a change of dimension. This new space is called "space redescription" (see Figure *3.4*). Indeed intuitively more the size of the redescription space, the greater the probability of finding a separating hyperplan between the examples is high.

Therefore there is a transformation of a nonlinear problem of separation in the representation space into a linear separation problem in a redescription space larger.

This non-linear transformation is performed using a kernel function.

In practice, some families of configurable core functions are known and it is for the SVM user to perform tests to determine which is most suitable for its application. Include the following examples of kernels:

•The linear kernel: is a simple scalar product: $k(x, z) = \langle x, z \rangle$

•The polynomial kernel: is used to represent boundaries by decision polynomials of degree d.

The generic form of this kernel is: $k(x, z) = (a * \langle x, z \rangle + b)^d$

•The kernel RBF (Radial Basis Function): widely used in practice nucleus that evaluates according

$$k(x, z) = e^{\frac{-\|x-z\|^2}{2\sigma^2}} \tag{3.4.1}$$

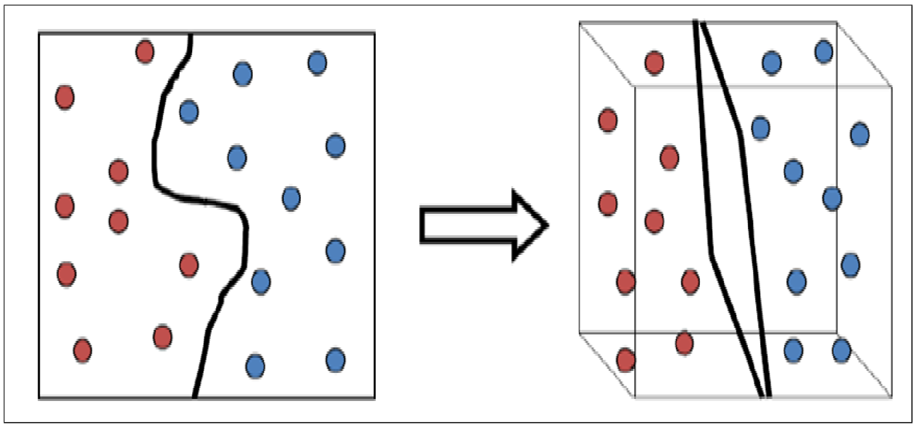


Figure 3.4 Transformation of the data in a large dimension space

Where σ is a positive real that represents the bandwidth of the kernel.

Classifiers expressed by a linear kernel are equivalent to linear separators expressed directly in the sample space (without using the core strategy).

Also the variables d and σ of the polynomial and RBF kernels are hyper parameters learning algorithms.

Their value greatly changes the type of generated decision borders and consequently the quality of the resulting classifiers.

3.5 Multi-class SVM

Originally, the SVM were designed primarily for 2-class problems, though several approaches to extend this algorithm to cases N classes were proposed.

The generalization in the multi-class cases can be done in three different ways.

The first two methods are based on a multiplication of two-class classifiers while the latter offers a comprehensive resolution.

- **Approach One against all(1vsR)**

The most natural approach is to use this method Binary discrimination and learn N functions of decision $\{f_m\}$ $m = 1...N$ to discriminate between each class for all other (each class is opposed to all the others) .

It must therefore ask N problems binaries. Assigning a new point x to a class C_i is through the relationship:

$$i = Arg_{(1 \leq m \leq N)} Max(f_m(x)) \tag{3.5.1}$$

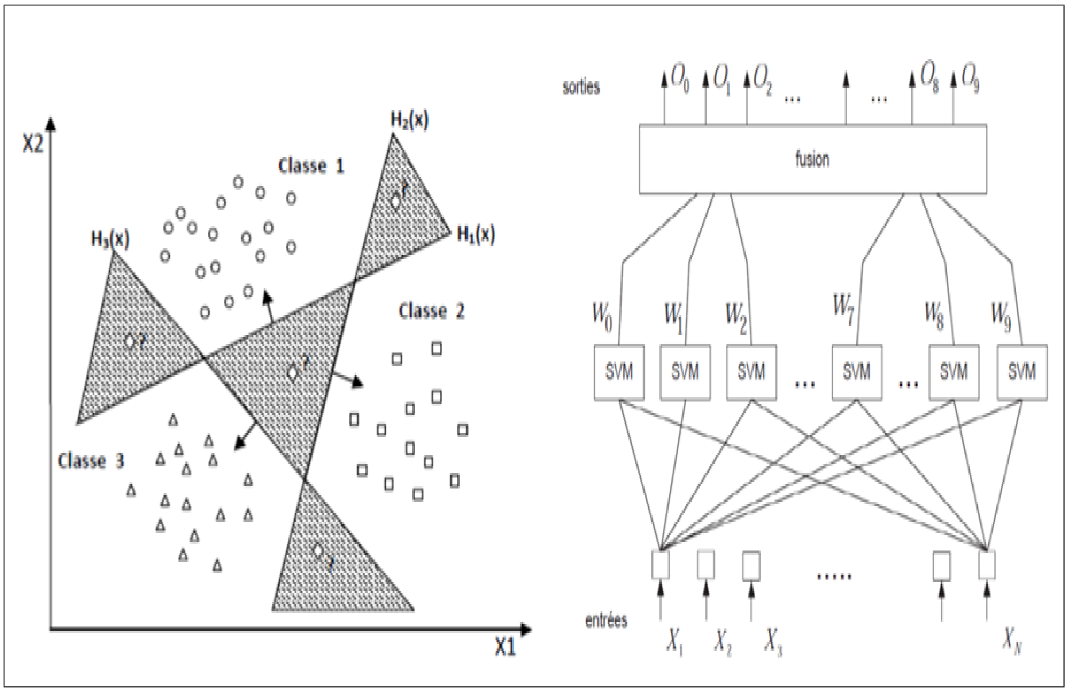


Figure 3.5 (left) Scatter 3 classes: one approach against all [57] (right) System Architecture Strategy A-against-all [33].

- **Approach one against one (1v1) [20]**

The approach one against one is a special case of decomposition methods proposed by Dietterich et al. Instead of learning decisions N functions, each class is discriminated by another.

Thus, $N(N-1)/2$ functions decisions are learned and each of them carries a vote for the appointment of a new point x.

The class of this point x then becomes the majority class after the vote.

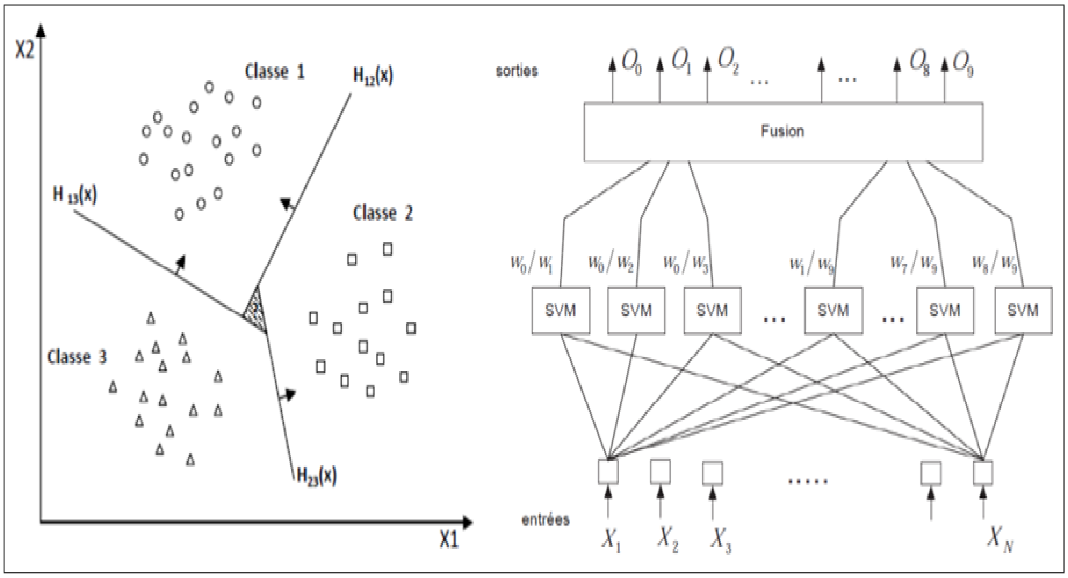


Figure 3.6 (left) Scatter 3 classes: one against one approach, (right) System Architecture Strategy one againstone[33].

- **Global method**

The last method is an approach extending the notion of margin in the multi-class cases. The problem involves n functions of decision and it is very greedy in computation time and memory space so it remains little used in actual cases.

3.6 Advantages and disadvantages

Advantages

- SVM have strong mathematical foundations.

- Test Examples are compared with just supports vector and not with all the training examples.
- Quick decision: classifying a new example is to see the sign of the decision function $f(x)$.

Disadvantages

- Binary classification of where the need to use the approach A-against-one.
- Large quantity of examples in entries implies a matrix calculation important.
- Calculation time high when a regularization of the problems of the kernel function

3.7 Conclusion

SVM is a classification method that shows good performance in solving various problems. This method has proven effective in many fields of applications such as image processing, text categorization or medical diagnostics and even on data sets of very large dimensions. Therefore the scope of the SVM is wide. They represent a class of very attractive methods.

This classification method is based on finding a hyperplane that separates the best data sets. In this chapter we have tried to present in a simple way and complements Support Vector Machines. We gave an overview of SVM, we exposed linearly separable case and non-linearly separable case. This method is applicable for classification tasks in two classes, but there are extensions for multi-class classification. The advantage of SVM is the selection of Support Vector representing discriminant a vector by which is determined the hyperplane. The examples used in the search of the hyperplane are no longer useful and only these support vectors are used to classify a new case.This makes it a very fast method.

Chapitre 4

Experimental results and discussion

4.1 Introduction

In this chapter, we introduce the environment of development and the different tools have been used. We describe the license plate recognition system, which includes six major phases: vehicle image acquisition, vehicle image pre-processing, license plate extraction, license plate pre-processing, character segmentation, and character recognition. Each phase includes several operations. Then we make a comparison between the performances of the classifiers used independently.

4.2 development environment

Matlab (R2014b)

Matlab and interactive environment is a high level language that allows execution of tasks requiring high computing power and whose implementation will be much easier and faster that with traditional programming languages such as C, C ++. it has several boxes in particular the tools of image processing "Porocessing Image Toolbox" offering a set of algorithm and reference graphics tools for processing, analysis, visualization, and algorithm development An image processing.

MATLAB is widely used as a computational tool in science and engineering encompassing the fields of physics, chemistry, math and all engineering streams. It is used in a range of applications including:

- signal processing and Communications
- image and video Processing
- control systems
- test and measurement
- computational finance
- computational biology

For the implementation of our application, we opted for the Matlab language use IDE (integrated development environment) Matlab R2014b, figure 4.1 presents the Matlab interface.

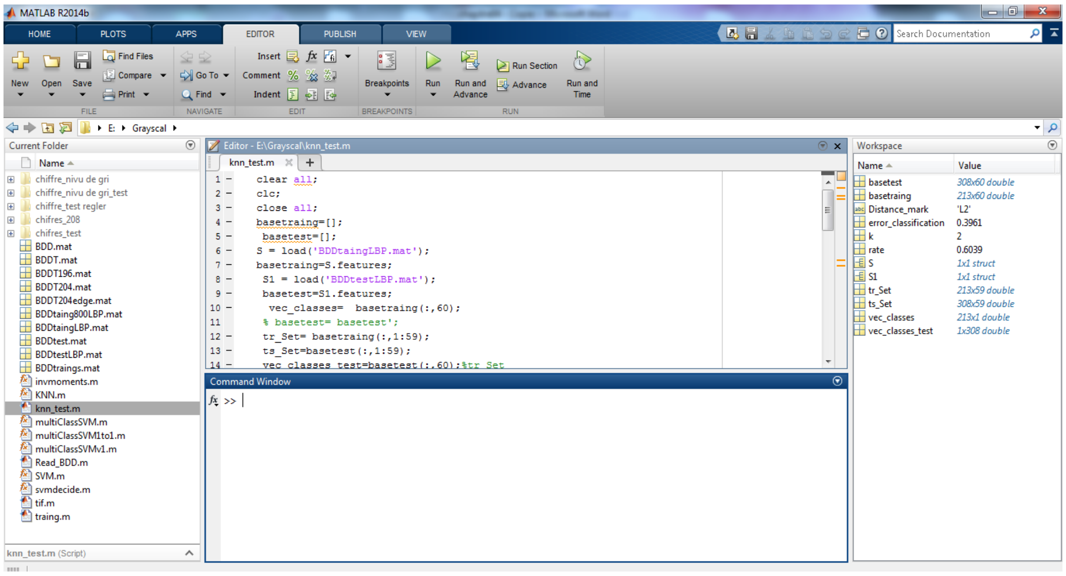


Figure 4.1 the Matlab 2014b interface.

4.3 Structure of the implemented system

The structure of our system is described in the following figure (Figure 4.2):

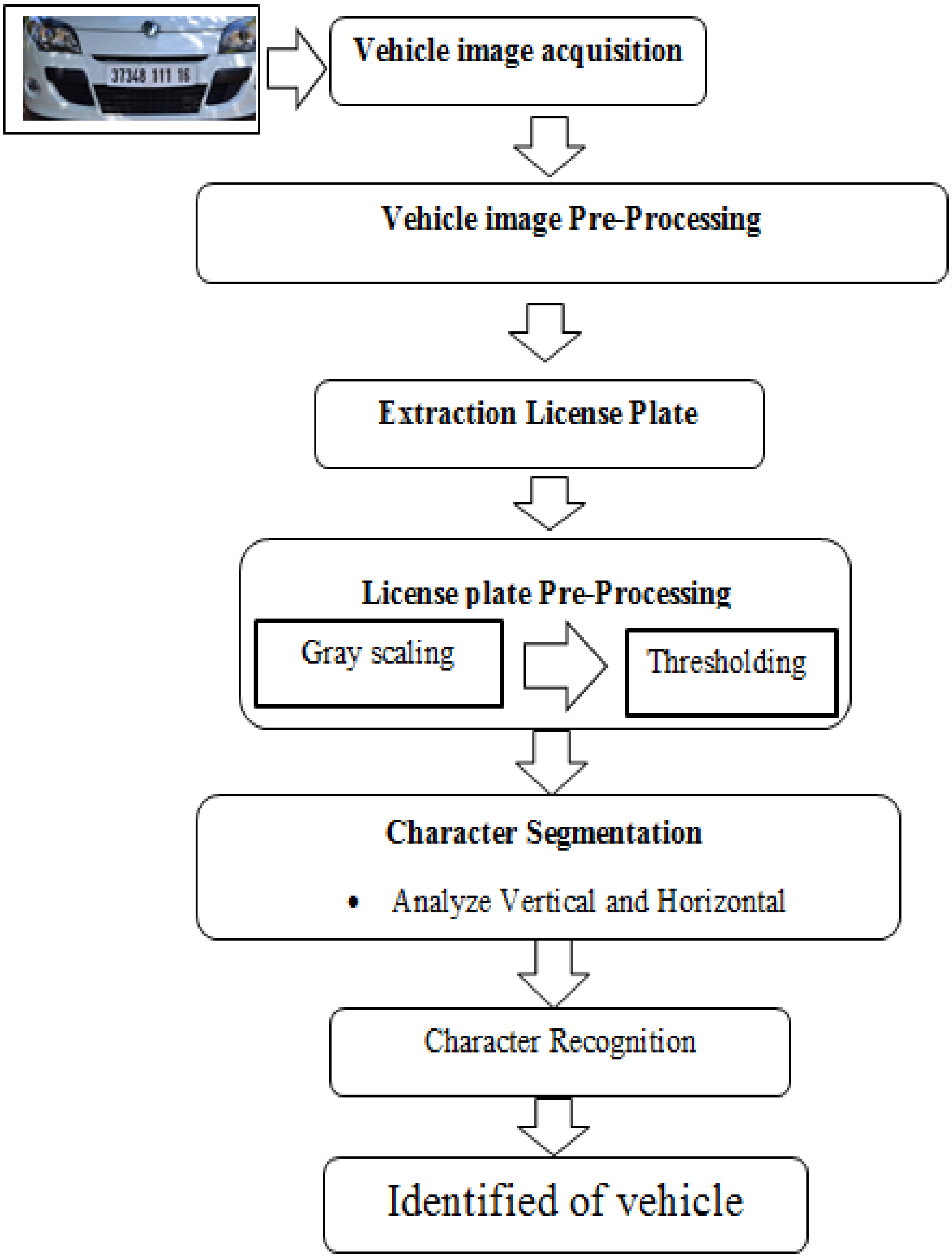


Figure 4.2 Structure of the implemented system.

4.3.1 Vehicle image acquisition

The images are captured in RGB format so it can be further processed for the number plate extraction. Then, resize the image keeping the aspect ratio same. In this work we have designed and used two databases:

Vehicle database: is contain fifteen images of front and back of vehicles and have resolution of 96 ppp ,prefondur color 24 and format jpeg . The figure 4.3 shows some examples from the dataset.

Figure 4.3 Input images (Captured image through own camera)

Images digit database: In this work we have used two Images digit database: the first contains binary images digits and the second contains graysclale images digits.

The first database contain (809) images and have size $(24, 42)$, resolution of 72 ppp ,prefondur color 1 and format .tif. And the second database contain (800) images and have size $(24, 42)$, resolution of 72 ppp ,prefondur color 8 and format tif . The figure 4.4 shows some examples of this dataset

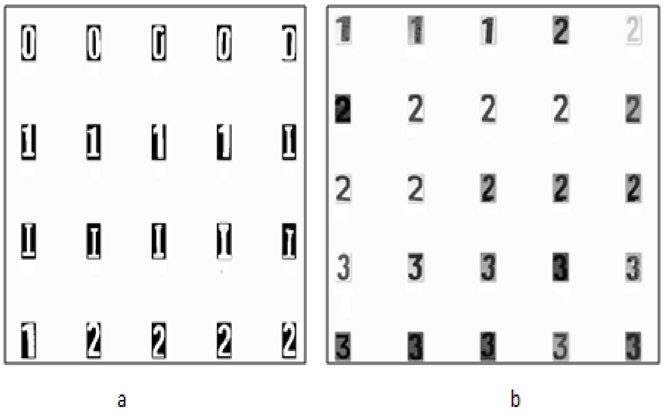


Figure 4.4 Some exempls of digit Images of databases used , (a)binary digit Images, (b) grays cal digit Images)

4.3.2 Vehicle image Pre-Processing

The image pre-processing is the important step in the recognition system, this step is essential to enhance the input image and make it more suitable for the next processing steps.

The figure 4.5 shows the four parts of this phase: graysclale level, Sobel masking, Normalization, Threshold (Otsu).

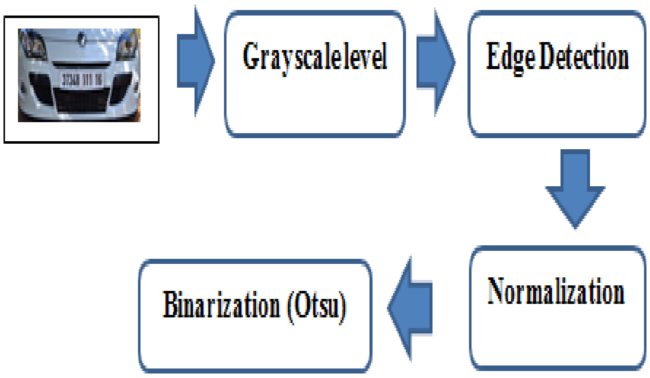


Figure 4.5 the preprocessing flow chart of vehicle image

Convert image to grayscale level

A grayscale image is a data matrix whose values represent intensities within some range. The image is converted to gray level to accelerate the image processing. Thus, in the picture, there will remain only black, white and gray values. The process needs to be done before the image is converted into binary level.

The image that is acquired from the camera can be an RGB colour image or a Grayscale Intensity image. The algorithm has to check for the RGB image and then has to convert it into a Grayscale image, because all the further processing is done in Grayscale format.

the RGB image is converted to gray scale image, Gray scale conversion: From the 24-bit color value of each pixel (i, j) the R, G and B components are separated and the 8-bit gray value is calculated using the formula: $gray(i, j) = 0.59 * R(i, j) + 0.30 * G(i, j) + 0.11 * B(i, j)$

Where, Gray shows the value of gray-scale image. R, G and B show the value of Red, Green, and Blue pixels, respectively. The figure 4.6 blow shows some examples of converted original images to grayscal images.

Figure 4.6 example Convert original images to grayscale images

Edge Detection by Using Sobel Operator

According to our observation, the location of the license plate usually has high contrast, this effect is due to the large differences between the values of two close pixels. The greater differences between two pixels, the better effect will be generated.

The Sobel operator or Sobel Filter, Technically, it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation that it produces is relatively crude, in particular for high frequency variations in the image.

The operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives - one for horizontal changes, and one for vertical. If we define A as the source image, and G_x and G_y are two images which at each point contain the horizontal and vertical derivative approximations, the computations are as follows:

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * A \text{ and } G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * A$$

Where here denotes the 2-dimensional convolution operation.

Since the Sobel kernels can be decomposed as the products of an averaging and a differentiation kernel, they compute the gradient with smoothing. For example, G_x can be written as :

$$\begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} -1 & 0 & +1 \end{bmatrix}$$

The x coordinate is defined here as increasing in the "right"-direction, and the y coordinate is defined as increasing in the "down"-direction. At each point in the image, the resulting gradient approximations can be combined to give the gradient magnitude, using:

$$G = \sqrt{G_x^2 + G_y^2} \tag{4.3.1}$$

Using this information, we can also calculate the gradient's direction:

$$\Theta = a \tan 2(G_x, G_y) \tag{4.3.2}$$

Where, for example,"Θ " is " 0 " for a vertical edge which is lighter on the right side. The mask chooses it's the horizontal operator:

-1	-2	-1
0	0	0
1	2	1

This mask will prominent the horizontal edges in an image. It also works on the principle of above mask and calculates difference among the pixel intensities of a particular edge. As the centre row of mask is consist of zeros so it does not include the original values of edge in the image but rather it calculate the difference of above and below pixel intensities of the particular edge. Thus increasing the sudden change of intensities and making the edge more visible[34].

In last, the result of Sobel horizontal operator, consider just value of edge and fray weak edge. The figure 4.7 blow shows some examples of converted original images to edge detection images using technique Sobel.

Figure 4.7 example Convert original images to edge images

Normalization

In image processing, normalization is a process that changes the range of pixel intensity values. Applications include photographs with poor contrast due to glare, for example. Normalization is sometimes called contrast stretching or histogram stretching. In more general fields of data processing, such as digital signal processing, it is referred to as dynamic range expansion.

The purpose of dynamic range expansion in the various applications is usually to bring the image, or other type of signal, into a range that is more familiar or normal to the senses, hence the term normalization. Often, the motivation is to achieve consistency in dynamic range for a set of data, signals, or images to avoid mental distraction or fatigue. For example, a newspaper will strive to make all of the images in an issue share a similar range of grayscale.

Normalization transforms an n dimensional grayscale image:

$$I : \{X \sqsubseteq \mathbb{R}^n\} \longrightarrow \{Min, ..., Max\} \tag{4.3.3}$$

With intensity values in the range (Min, Max) into a new image:

$$I_N : \{X \sqsubseteq \mathbb{R}^n\} \longrightarrow \{newMin, ..., newMax\}$$

With intensity values in the range (newMin, newMax).

The linear normalization of a grayscale digital image is performed according to the formula:

$$I_N = (I - Min)\frac{newMax - newMin}{Max - Min} \tag{4.3.4}$$

Binarization(Otsu)

We use the Otsu threshold to binarize the candidate regions and count the connected components which are almost perpendicular to the dominant plate direction.

In computer vision and image processing, Otsu's method, is used to automatically perform clustering-based image thresholding, or, the reduction of a graylevel image to a binary image. The algorithm assumes that the image contains two classes of pixels following bi-modal histogram (foreground pixels and background pixels), it then calculates the optimum threshold separating the two classes so that their combined spread (intra-class variance) is minimal, or equivalently (because the sum of pairwise squared distances is constant), so that their inter-class variance is maximal.

In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes:

$$\sigma_w^2(t) \ = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \tag{4.3.5}$$

Weights w_i are the probabilities of the two classes separated by a threshold t and σ_i^2 are variances of these classes.

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = w_1(t) + w_2(t) \left[\ \mu_1(t) + \mu_2(t)\right]^2 \tag{4.3.6}$$

Which is expressed in terms of class probabilities w_i and class means μ_i. The class probability $w_1(t)$ is computed from the histogram as t:

$$w_1(t) = \sum_0^t p(i)$$

While the class mean is:

$$\mu_1(t) = \left[\sum_0^t p(i) * x(i)\right] / w_1 \tag{4.3.7}$$

Where $x(i)$ is the value at the center of the $i-$th histogram bin. Similarly, you can compute $w_2(t)$ and μ_2 on the right-hand side of the histogram for bins greater than t.

The class probabilities and class means can be computed iteratively. This idea yields an effective algorithm.

Algorithm

1. Compute histogram and probabilities of each intensity level.
2. Set up initial $w_i(0)$ and $\mu_i(0)$.
3. Step through all possible thresholds $t = 1......$ *maximum intensity*
   (a) Update w_i and μ_i.

(b) Compute $\sigma_b^2(t)$.

4. Desired threshold corresponds to the maximum $\sigma_b^2(t)$.

5. You can compute two maxima (and two corresponding thresholds).$\sigma_{b1}^2(t)$ is the greater max and $\sigma_{b2}^2(t)$ is the greater or equal maximum .

6. Desiredthreshold= $\dfrac{threshold_1 - threshold_2}{2}$.

Finally, after the application of Otsu algorithm in car image, we take a binary image with a threshold automatic[35].

4.3.3 Extraction License Plate

Number plate detection is the key step of vehicle identification system. The goal of this phase, given a frame captured from input video is to produce the region with high probability of containing the number plate area.

This problematic includes algorithms that are able to detect a rectangular or square area of the plate in an original image. Humans define a number plate in a natural language as a “small plastic or metal plate attached to a vehicle for official identification purposes”, but machines do not understand this definition as well as they do not understand what “vehicle”, “road”, or whatever else is. Because of this, there is a need to find an alternative definition of a number plate based on descriptors that will be comprehensible for machines. This step is dividing to two phases:

Mathematical Morphology

The algorithm uses morphological operations on the pre-processed, edge images of the vehicles. The basic morphological operations are erosion and dilation, dilation is used to fill the gaps or holes. We use a morphological operator for image of once dilated horizontally and the other time vertically.

Another horizontal dilation is employed on the common bright pixels. The structuring elements of dilations are pixel horizontal or vertical lines. Due to digits and characters, a license plate contains many vertical edges. This feature is employed for locating the plate in an image. Many approaches have been proposed for edge detection. Sobel mask has a good performance compared with others; indeed, it is fast and simple. In general, there are two masks for Sobel, horizontal mask and vertical one. Closing also tends to smooth sections of contours but, as opposed to opening, it generally fuses narrow breaks and long thin gulfs, eliminates small holes, and fills gaps in the contour. The most important step in this phase are:

Horizontal Projection Histogram: Although projection histogram is not a new concept, it is used here to find the upper and lower bounds of a binary image after the vertical edge are obtained. We perform a horizontal projection to find the top and bottom position of license plate area. When all values of histogram bins along all lines in the horizontal direction are computed, the horizontal projection histogram is obtained. The mean value of the histogram is then used as a threshold to figure out where the upper bound and lower bound are. The horizontal projection histograms of the sample image is displayed in Figure 4.8 .Finally, the distance between upper and lower boundaries is recorded as the height value of probably license plate area.[4]

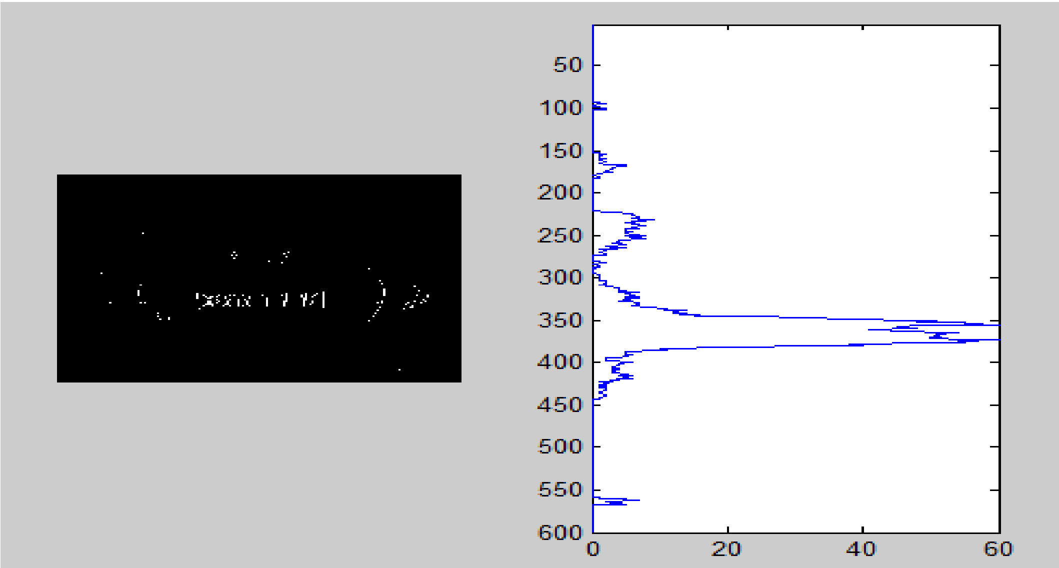


Figure 4.8- Edge Horizontal Histogram

Threshold on Edge Histogram and Candidate Plate Rows: The threshold obtained from the horizontal histogram is 350 because is the highest value in the histogram.

The output image from the previous stage consists of a set of groups of connected pixels. A labelling algorithm can be used to mark these pixels. Once all groups of pixels have been determined, each pixel is labelled based on the group it belongs to. Therefore, a set of potential candidates can be selected from the image using the known geometrical conditions. A validation process needs to be used to extract the candidate that represents the licence plate.[4]

Masked Plate: The goal of this step is to determine which one of segments extracted from the image segmentation process represents the LP region in the digital image. Since the LP has a rectangular shape, then, an algorithm has been proposed and applied to specify whether the tested segment has a semi like rectangular shape similar to that of LP depending on certain features computed for that segment.

The first feature that used to classify segments is the segment size feature. That means, if a segment is too small (i.e., consist of a very few number of pixels) it will be ignored; otherwise this segment will be considered as LP candidate and other features will be extracted from it in the next stages. When the segment has an acceptable size, then the following will be applied on it:

A) The whole segment will be scanned to find four parameters values: (1) the minimum x value (Xmin), (2) the maximum x value (Xmax), (3) the minimum y value (Ymin) and (4) the maximum y value (Ymax).

B) For every column starting from Xmin to Xmax, all the lowest Y values and all the highest Y values will be stored in two different arrays; both are one dimensional (1D) arrays. The difference between the corresponding elements of these two arrays will be stored in one dimensional array with an index starting from Xmin and ending with Xmax.

C) Then, the values of Y differences will be sorted in an ascending order. Then the first%2 and the last %2 of the sorted values are omitted because they may hold abnormal values of the Y differences.

D) The mean and the standard deviation are calculated for the remaining %96 of the Y differences. If the tested segment has a rectangular shape, then the value of the determined standard deviation should be small. Also, its determined average object height (i.e. mean of the differences in Y) should not be small.

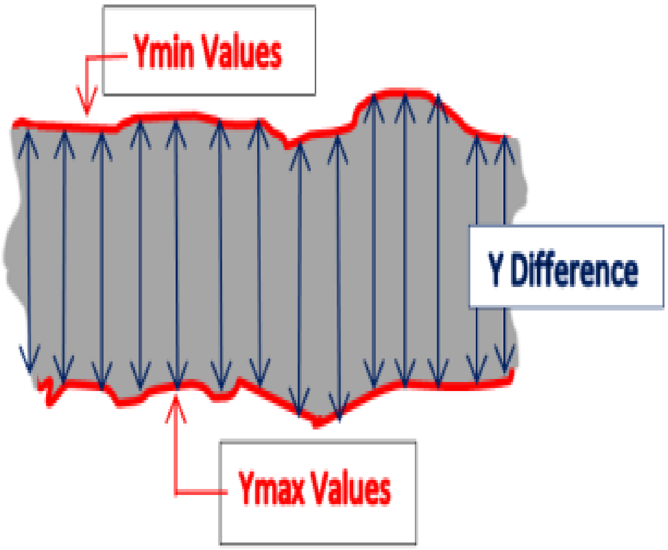


Figure 4.9 The height variability of a tested segment

E) In the same way, the above mentioned (B, C, and D) steps will be applied on the X differences. For every row lay within the range [Ymin to Ymax] in the candidate segment the left most X values and the right most X values will be allocated and stored in two different 1D arrays, then the difference between the corresponding elements of these two arrays will be stored in another 1D array. The elements of this array will be sorted and only the mid %96 of the sorted values will be used to calculate the mean and the standard deviation for differences in X. If the tested segment is the **LP** then the average width of it should not be small. [4]

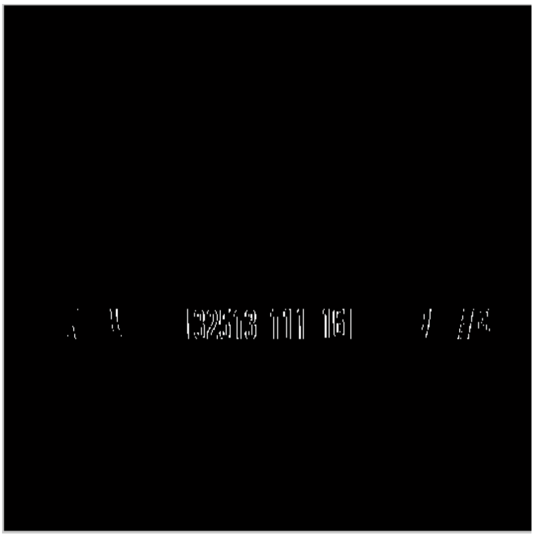


Figure 4.10 Masked plate

Morphology (Dilation - Vertical) (Dilation - Horizontal) **Dilation:** The image is subjected to dilation. The effect of the operation on a binary image is, it gradually enlarge the boundaries of regions of foreground pixels (i.e. white pixels, typically). Thus areas of foreground pixels grow in size while holes within those regions become smaller.

$$A \oplus B = \{z | [(B)z \cap A] A\}$$

Where A = original image, B = Structuring element

$$\begin{matrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{matrix}$$

Now we use a morphological operator. The image of figure 4.11 is once dilated horizontally and the other time vertically.

Another horizontal dilation is employed on the common bright pixels of these two dilated images. The structuring elements of dilations are 6-pixel horizontal or vertical lines.[4]

As we want to obtain a continuous region as the plate location, in this part of algorithm, the probable holes are filled. Figure 4.11 illustrates the filling operator result.

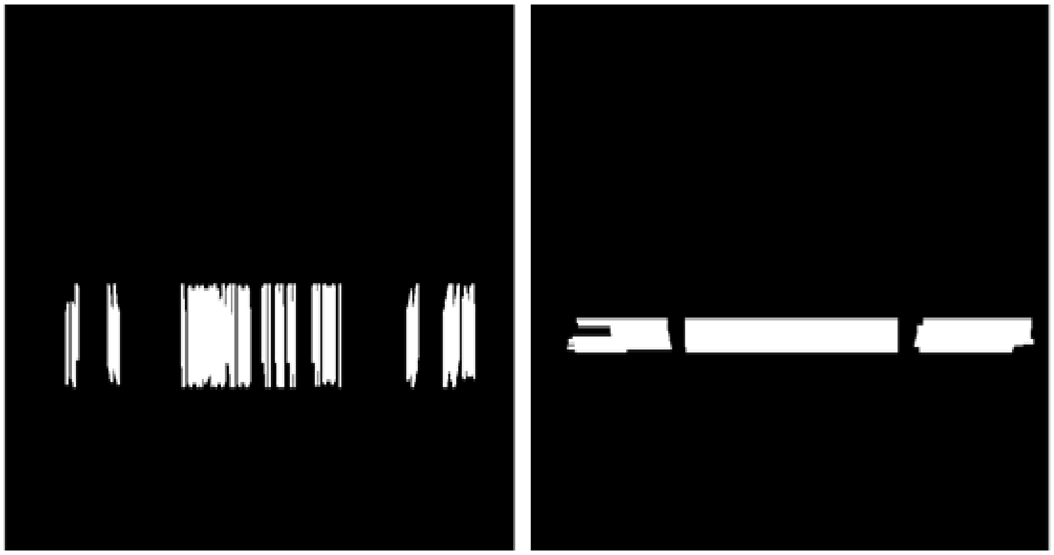


Figure 4.11 Morphology (Dilation Vertical) and Morphology (Dilation Horizontal)

It's the result of intersection between Morphology (Dilation Vertical) and Morphology (Dilation Horizontal).

Area_Common = (**DilationVertical**) $\cap$ (**Dilation Horizontal**).

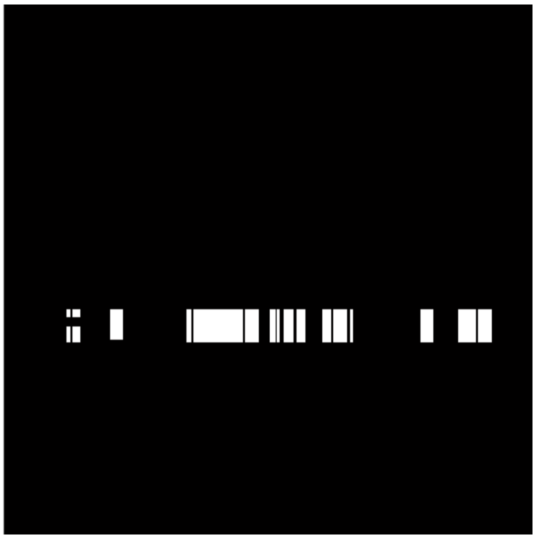


Figure 4.12 The Joint Places.

Then the finding of the common areas between Dilation Vertical and Dilation Horizontal, do a dilation of this area.

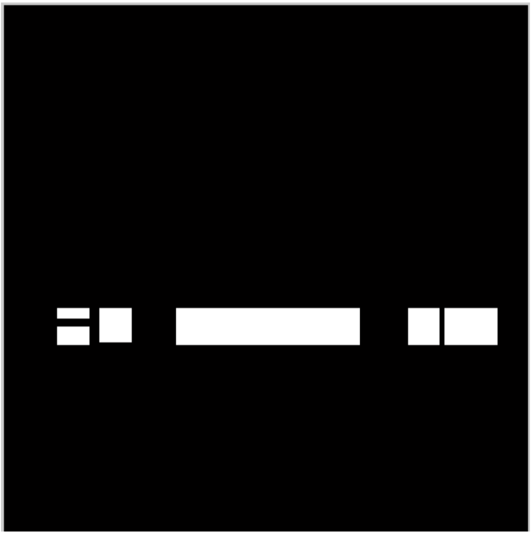


Figure 4.13 Dilation of joint place

Erosion: Erosion operator excludes any extra regions, which do not belong to the plate. We erode the image with a horizontal band (a 5*40 rectangle). Any regions smaller than this band are totally omitted from the candidate regions.

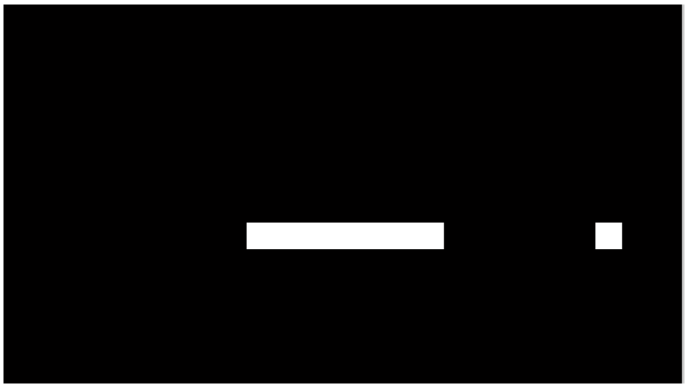


Figure 4.14 the result of erosion.

Plate location

After the mathematical morphology operations we most localize the plate in image according to the biggest Binary Region.

The result of combination of two top-hats contains not only letters of number plate but also a lot of other unwanted image elements. In order to detect the proper area, the directional filtering is then applied. The choice of such filters was motivated by the fact that main axes of car number plates are parallel to the main axes of image coordinate system. Due to a short distance between consecutive characters some deviations from the parallel position are allowed and – if they are not too big (not bigger that approximately 10 degrees) – they don't disturb the detection process.

Plate=max (Binary_Area).

Figure 4.15 plate isolation

4.3.4 License plate Pre-Processing

After license plate localization, the output image has been converted to grayscale image. then to binary image by thresholding method.

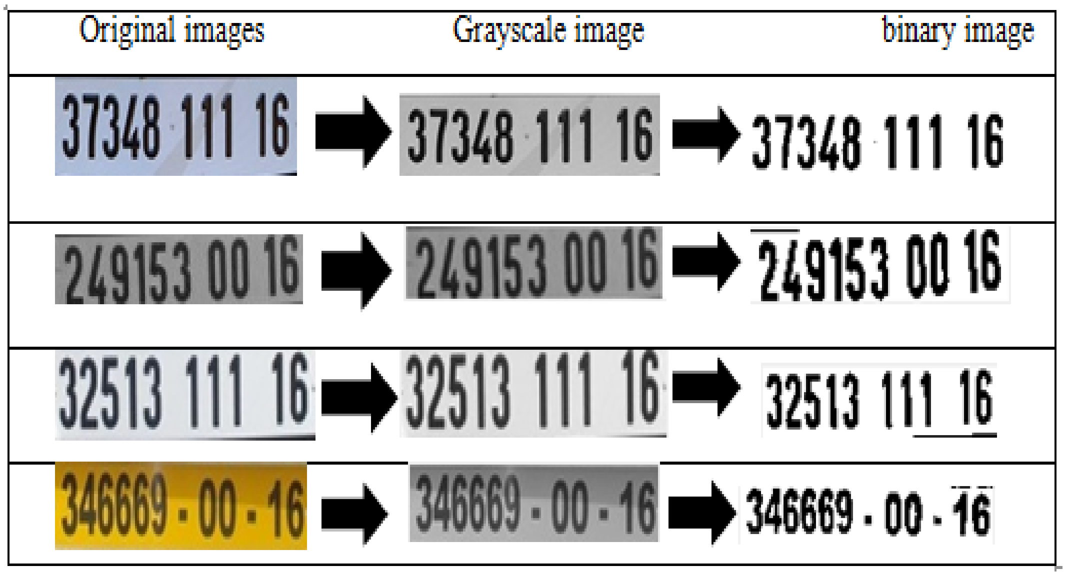


Figure 4.16 exemple of convert original license plate to image gray scale

4.3.5 Character Segmentation

After license plate location, character segmentation process was carried out to extract the characters from the plate region before proceed into character recognition process.

To get individual character and number image by using, vertical and horizontal histogram projection method.

Vertical Scanning: Vertical scanning technique is used to dig out each character from the image found on one first and last column part. It's into the image by part vertically from [0,0] until [width, height] that is dead in columns by column scanning. as a result of the input image can be a binary image that comprises one and 0 values, vertical scanning theme is simple to be dead. The scale between each first and last column area unit about to be computed. At last, every character or varieties area unit about to be slice to separate it from the plate background. Every component goes to be kept in array individually for next horizontal scanning method.

Horizontal Scanning: One each component is saved individually in preceding step, horizontal scanning will verify the first and last rows of the image. The intention is to eradicate additional higher and lower region from the image. To conclude, the tip results of this technique area unit about to be an image with filler with character or vary elements with none spare areas. The Figure4.17 represented vertical and horizontal scanning of license plat and The Figure4.18 represented character segmentation

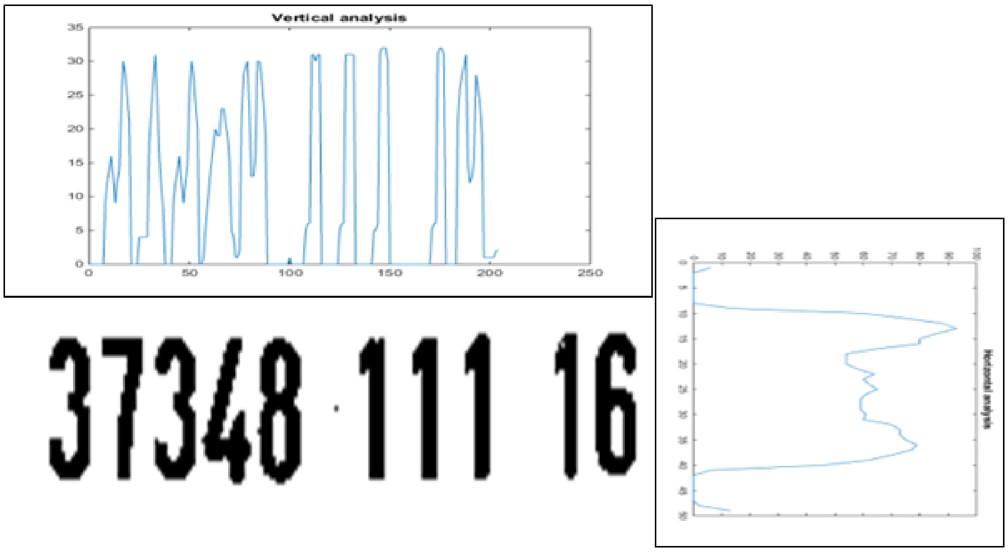


Figure 4.17 vertical and horizontal scanning of license plate.

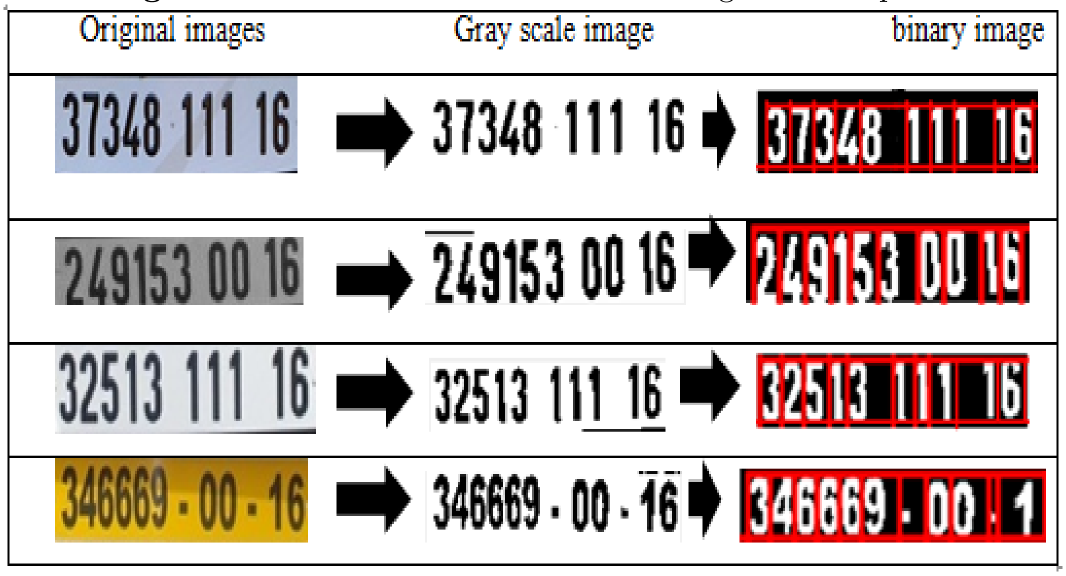


Figure 4.18 exemple of character segmentation

Normalization

the normalization of image is to transform the image size and fit a fixed size a priori by the user, for this we have proposed a procedure to normalize the images used in a size of 42x24 pixels . Was applied to the images of our base as the image segmentation result

Figure 4.19 Normalisation of digit "3"

4.3.6 Character Recognition

After segmenting the characters, the next step is character recognition. this step divised in tow step feature extration and character recognition

Feature extraction

The very important role in each ANLP system is the features extraction, especially for license plate recognition, in fact the precision of an certain system recognition depends heavily to features extraction operation in reason of if an great discrimination between characters is truly realized its recognition will be at that time very correct. In this framework, we have chosen to use two methods of feature extraction for recognition of Algeria plate which are:

Hu invariant moment: In our work we chose to use Hu moments on the binary database. The following Figure 4.20 shows some results obtained through the exploitation of Hu Invariant Moments.

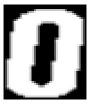
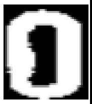
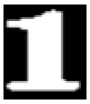
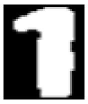
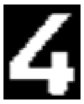
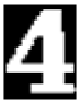
digit / Hu moment	0		1		4		9	
								
I1	0,2834	0,2997	0,3194	0,3174	0,3513	0,2968	0,2897	0,3461
I2	0,0222	0,0217	0,05742	0,0646	0,0331	0,0330	0,02573	0,0375
I3	6,012e-06	1,30e-05	0,00053	0,0028	0,02440	0,0044	0,0003	0,0052
I4	8,55e-07	4,24e-06	2,64e-05	0,0006	0,0050	0,0001	0,0001	0,0009
I5	1,741e-12	2,32e-11	-2,59e-09	8,26e-07	5,35e-05	7,57e-08	1,125e-08	1,92e-06
I6	1,59e-08	6,26e-07	-1,23e-06	0,00015	0,0007	8,79e-06	9,61e-06	0,00016
I7	8,509e-13	-2,14e-11	1,77e-09	-4,42e-07	-1,79e-05	-9,25e-08	-1,96e-08	-8,431e-07

Figure 4.20 some results of Hu Invariant Moments.

Local Binary Pattern: This technique introduces a algorithm of the feature extraction based on the LBP (Local Binary Pattern) operator. The original version of the local binary pattern operator works in a 3×3 pixel block of an image. The pixels in this block are thresholded by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. The some results of this step is shown in the following :

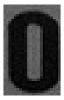
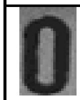
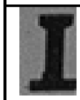
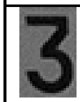
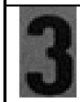
	Local Binary Pattern									
	0,23640	0,04329	0,00813	0,12531	0,00394	0,04018	0,00574	0,10695	0,01349	0,00695
	0,02886	0,03216	0,03986	0,00950	0,02809	0,00452	0,02409	0,08460	0,00763	0,05526
	0,10674	0,05047	0,01769	0,05061	0,04650	0,06313	0,04748	0,07805	0,14746	0,05273
	0,04337	0,03339	0,04736	0,03526	0,02560	0,19011	0,01483	0,02295	0,01269	0,13128
	0,02427	0,01980	0,02272	0,02426	0,01977	0,01599	0,01033	0,03309	0,02731	0,03849
	0,05086	0,04154	0,10298	0,03347	0,06026	0,04524	0,14076	0,57442	0,63482	
	0,28963	0,03715	0,00000	0,09536	0,00447	0,04366	0,00706	0,07492	0,00796	0,01668
	0,02373	0,00774	0,01649	0,03443	0,03801	0,02755	0,02458	0,03276	0,01060	0,05193
	0,11875	0,02026	0,03261	0,03818	0,14899	0,06169	0,05465	0,17627	0,17879	0,04583
	0,04656	0,21752	0,15375	0,02477	0,02411	0,17630	0,02776	0,06233	0,04148	0,21295
	0,03888	0,02463	0,02269	0,01776	0,04480	0,04042	0,02604	0,01975	0,02840	0,04775
	0,04278	0,03025	0,05122	0,01931	0,03863	0,01893	0,06478	0,43723	0,63790	
	0,04391	0,02057	0	0,02408	0,0064	0,01729	0,000	0,03137	0,000	0,00615
	0,00386	0,00456	0,00344	0,01369	0,0000	0,01340	0	0	0,01179	0,03016
	0,07245	0,02542	0,00798	0,01209	0,10830	0,01000	0,04070	0,16643	0,05177	0,02575
	0,01569	0,15165	0,05738	0,04996	0,02029	0,19855	0,01758	0,06897	0,01565	0,23495
	0,01589	0,02383	0,00872	0,00814	0,00560	0,00627	0,00851	0,01778	0,00635	0,02636
	0,02575	0,03479	0,06577	0,02173	0,00894	0,00249	0,04270	0,79733	0,40956	
	0,25723	0,07629	0,00373	0,09389	0,02059	0,07509	0,01238	0,09394	0	0,02210
	0,00952	0,01076	0,00867	0,01774	0,01248	0,01444	0,01145	0,03439	0,05009	0,04377
	0,05137	0,05236	0,02823	0,02211	0,04522	0,07765	0,05947	0,14851	0,04385	0,02311
	0,05894	0,11232	0,01885	0,09241	0,01543	0,10131	0,03161	0,05270	0,01928	0,07993
	0,01212	0,01561	0,03329	0,06081	0,01489	0,02008	0,04884	0,03166	0,01852	0,02959
	0,05152	0,01736	0,12530	0,01453	0,04226	0,03676	0,10970	0,50858	0,71062	
	0,33581	0,09798	0,01615	0,05127	0,00810	0,08050	0,0000	0,05182	0,0000	0,01125
	0,00722	0,01596	0,00236	0,02397	0,00295	0,00863	0,01177	0,01896	0,03805	0,04666
	0,01308	0,03786	0,03352	0,03994	0,01076	0,05261	0,04342	0,07479	0,07035	0,0509
	0,02854	0,07851	0,08763	0,07218	0,05465	0,05713	0,04098	0,06963	0,04396	0,03323
	0,03074	0,02078	0,01141	0,02063	0,02131	0,02414	0,01959	0,01151	0,01443	0,04179
	0,06335	0,05439	0,05159	0,01801	0,09207	0,01922	0,07423	0,46206	0,74769	
	0,30599	0,05949	0,01448	0,10894	0,00532	0,05713	0,0000	0,13245	0,00502	0,03642
	0,01091	0,02687	0,02222	0,01149	0,02853	0,00679	0,01346	0,06001	0,02999	0,04131
	0,03662	0,05235	0,01972	0,04173	0,01231	0,05068	0,06541	0,06500	0,07182	0,05907
	0,03252	0,07453	0,08027	0,03649	0,02832	0,08313	0,06379	0,06814	0,02731	0,09132
	0,06069	0,01789	0,01268	0,02274	0,01445	0,02052	0,0313	0,05674	0,05153	0,03630
	0,04195	0,02452	0,10275	0,05833	0,07169	0,03717	0,10625	0,52547	0,68564	0,04195

Figure4.21 some result of LBP for digit images grays Cal.

Classification

After the features extraction, we designed a classifier based SVM and KNN for.

4.4 Performance measure of the recognition system

Generally, the performance of the license plate system is measured by false rejection rate (FRR), total error rate (TER) and rate recognition (RR) is determined by:

Rate recognition RR is the measure of the likelihood that the system will incorrectly accept an access attempt .

The false rejection rate, or FRR, is the measure of the likelihood that the system will incorrectly reject an access attempt .

$$RR = \frac{\text{number of reconized digits}}{\text{the size of database test}} \times 100\%$$

$$FRR = \frac{\text{number of not reconized digit}}{\text{the size of database test}} \times 100\%$$

4.5 Experimental studies

We designed a classifier based SVM and KNN, overs the first category based SVM classifiers is designed (2) variants of SVM one to all .

4.5.1 SVM One to all 2 variants

1. First variant to calculate the decision function for a classification with a support using parameters from the structure (SupportVectors, Alpha, Bias, KernelFunction, KernelFunctionArgs, scaleFactor, shift) for the decision using sign function, this function return (1 or 0)

2. the second using the function svmclassify(SVMStruct,Sample) classify vectors x according to the following equation:

$$c = \sum_i a_i k(s_i, x) + b)$$

Where s_i are the support vectors, a_i are the weights, b is the bias, and k is a kernel function. If $c \geq 0$, then x is classified as a member of the first group, otherwise it is classified as a member of the second group.

We used two (2) variants on the two (2) databases, as follows:

For the binary base we was taken Hu Invariant Moments on images and they even on images with edge detection, and for the base Grays cal we was applied LBP method for the extraction of characteristics.

The following table (4.1) represents the rate of recognition by class and total with and without edge detection using : two (2) variants of SVM one to all for classification.

		SVM One To All (v1)		SVM One To All (v2)	
	Number of Images	without edge detection	with edge detection	without edge detection	with edge detection
0	18	78%	72%	94%	89%
1	92	100%	100%	100%	96%
2	9	44%	55%	33%	44%
3	9	33%	33%	11%	33%
4	9	67%	66%	55%	67%
5	9	11%	11%	11%	22%
6	17	82%	82%	94%	29%
7	19	100%	100%	100%	100%
8	13	85%	75%	61%	00%
9	9	00%	10%	00%	00%
Total recognition rate		80%	77%	79%	70%

Table 4.1 the recognition rate by class and global with and without edge detection using two (2) variants of SVM one to all

Figure 4.22 represent the graphics recognition rate by class and global with and without edge detection using two (2) variants of SVM one to all

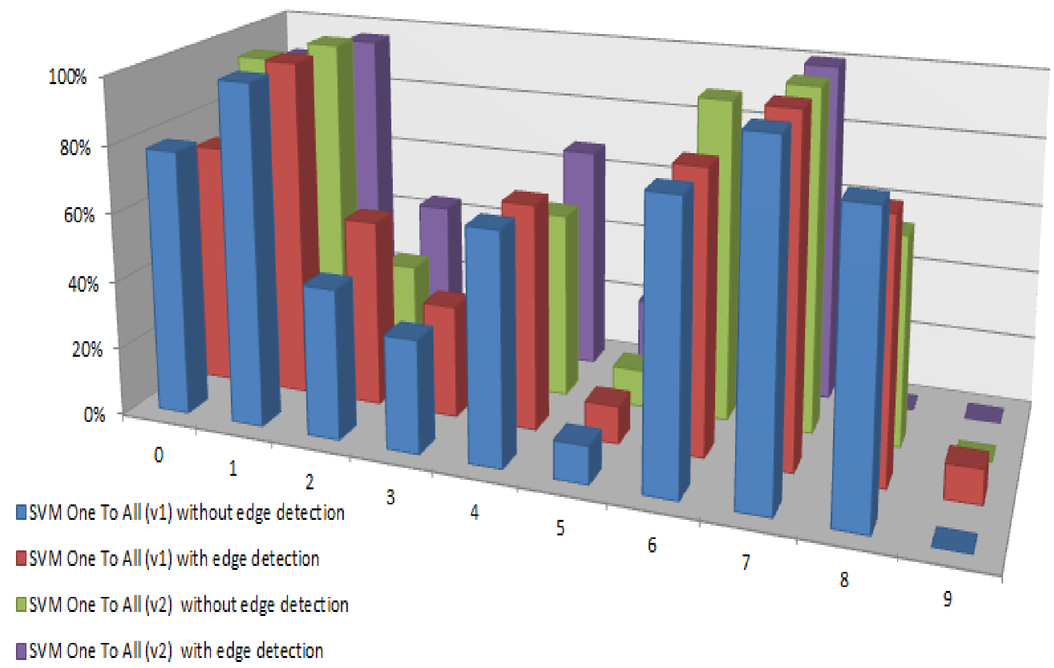


Figure 4.22 graphic of recognition rate by class

Figure 4.23 represent the graphics global recognition rate.

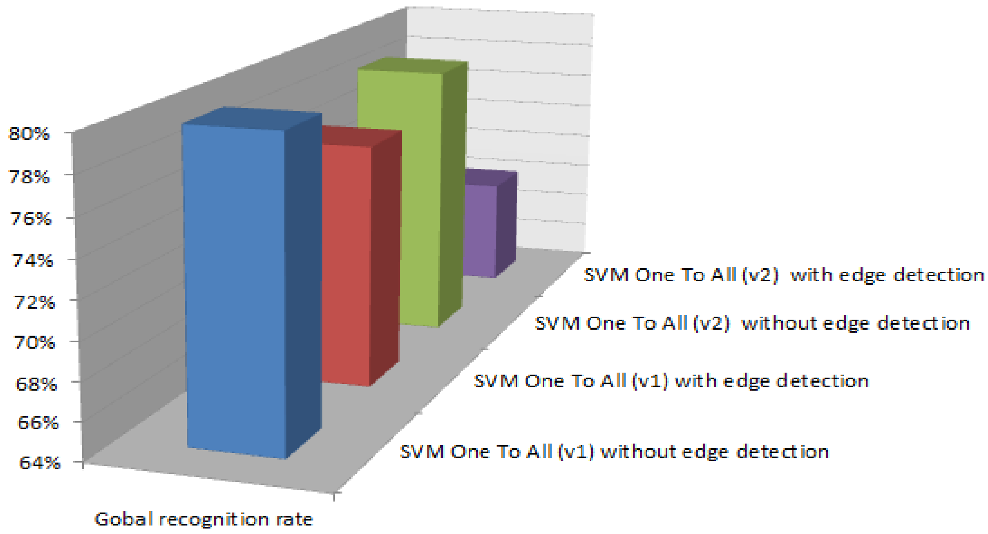


Figure 4.23 global recognition rate

We have found that the Hu Invariant Moments of images without edge detection SVM One to All (v1) gives the best recognition rate of 80% compared with the Hu Invariant Moments of images without edge detection SVM One To All (v2) 79%.

We have found that the Hu Invariant Moments of images with edge detection SVM One To All (v1) gives the best recognition rate of 77% compared with the Hu Invariant Moments of images with edge detection SVM One To All (v2) 70%.

We have compared between SVM One to All (v1) and SVM One To All (v2) classified methods; we have found also that Hu Invariant Moments of images without edge detection 80 % outperforms.

The following table represents the recognition rate by class and total for LBP using two (2) variants of SVM one to all for classification, and Figure 4.24 represent the graphic of recognition rate by class for LBP using two (2) variants of SVM one to all

	Number of Images	SVM One To All (v1)	SVM One To All (v2)
0	18	96%	00%
1	92	0.98%	00%
2	9	87%	87%
3	9	92%	92%
4	9	88%	88%
5	9	85%	85%
6	17	00%	00%
7	19	100%	100%
8	13	88%	88%
9	9	96%	96%
Total recognition rate		55%	47%

table 4.2 the rate of recognition by class and global for LBP using two (2) variants of SVM one to all

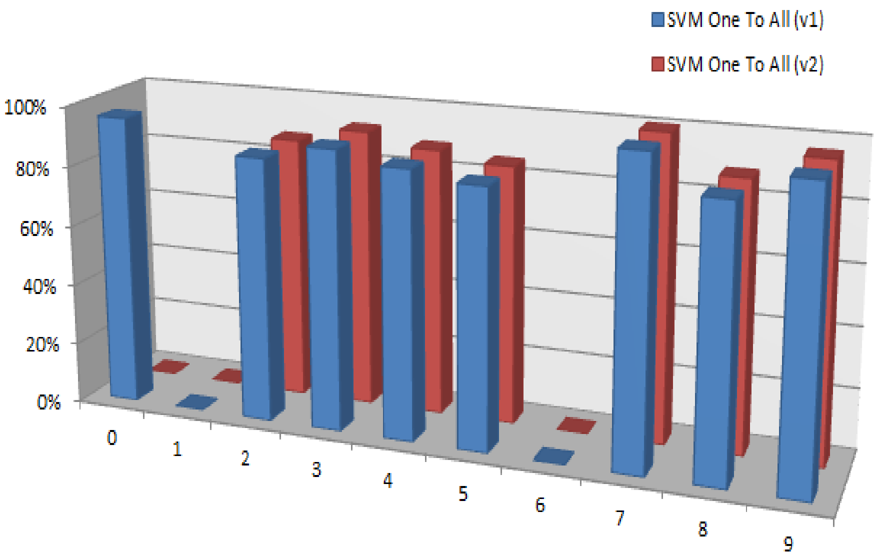


Figure 4.24 graphic of the recognition rate by class

Figure 4.25 represent the graphic of global recognition rate for LBP using two (2) variants of SVM one to all.

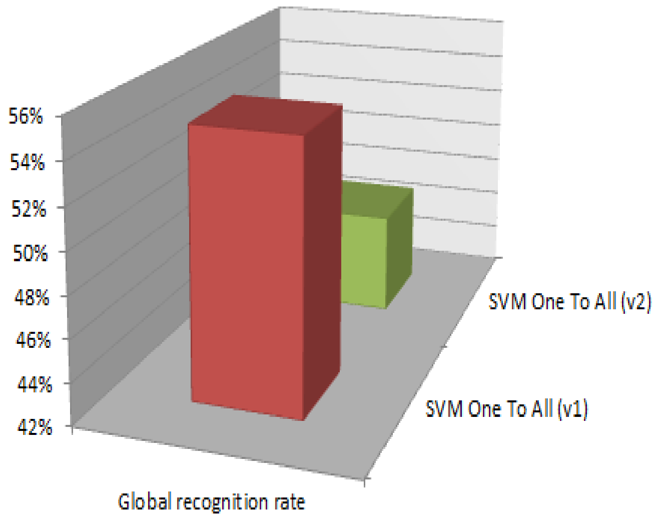


Figure 4.25 graphic of global recognition rate

We have found that the LBP using SVM One to All (v1) the best recognition rate of 55% compared with using SVM One To All (v2) 47%.

4.5.2 KNN

In this set of experiments, we have implemented LBP and Hu Invariant Moments methods using (L1 distance, Euclidean Distance or L2 Distance, Cosine or Negative Angle). All experimental results are summarized in table (4.3) and the Figure 4.26 presented the graph of this table.

		Distance		
		Cos	**Euclidean (L2)**	**L1**
Images binary (Hu moment)	without edge detection	71%	71%	73%
	with edge detection	78%	78%	77%
Grays Cal images (LBP)		60%	60%	58%

Table 4.3 the recognition rate for LBP and Hu Invariant Moments using KNN

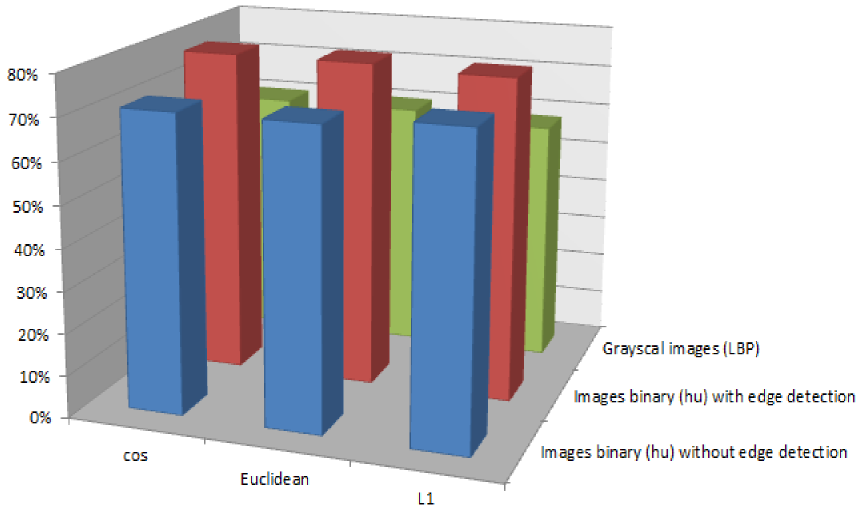


Figure 4. 26 graphic of recognition rate.

We have found that the images edge using Cos distance gives the best recognition rate of 78% compared with other images type.

We have found that the images edge using Euclidean distance gives the best recognition rate of 78% compared with other images type.

We have found that the images edge using L1 distance gives the best recognition rate of 77% compared with other images type.

4.6 Application

Our application contain many graphical interfaces, each one contains buttons and menus.

The main interface is given in figure 4.27.

In the File menu we can load, save a vehicle image or exit from the application.

Figure 4. 27 the Main interface.

if you click on the buttons extraction license plate go to the interface of the figure 4.28 is presented the interface of extraction license plate step.

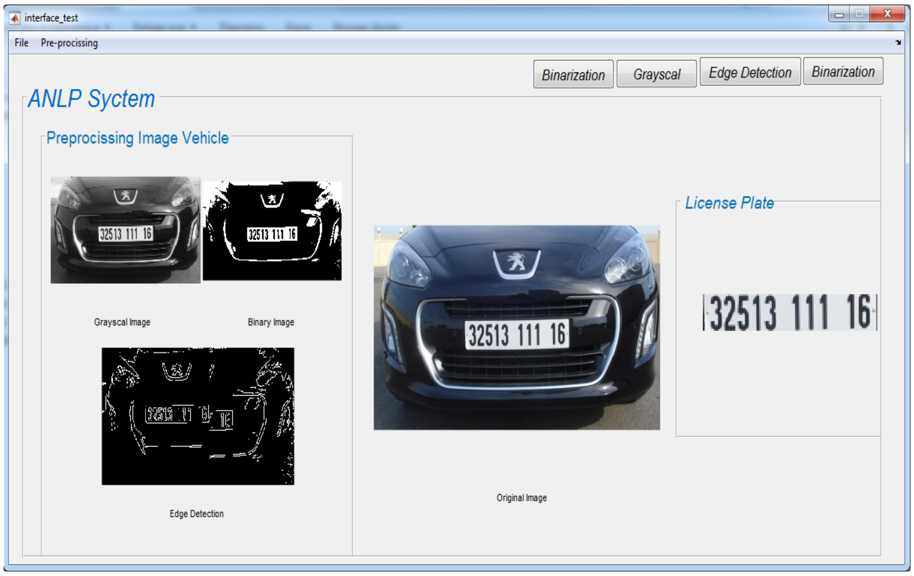


Figure 4.28 location plate

in menu interface if you click on the buttons character segmentation go to the interface of the figure 4.29 is presented the interface of character gementation step.

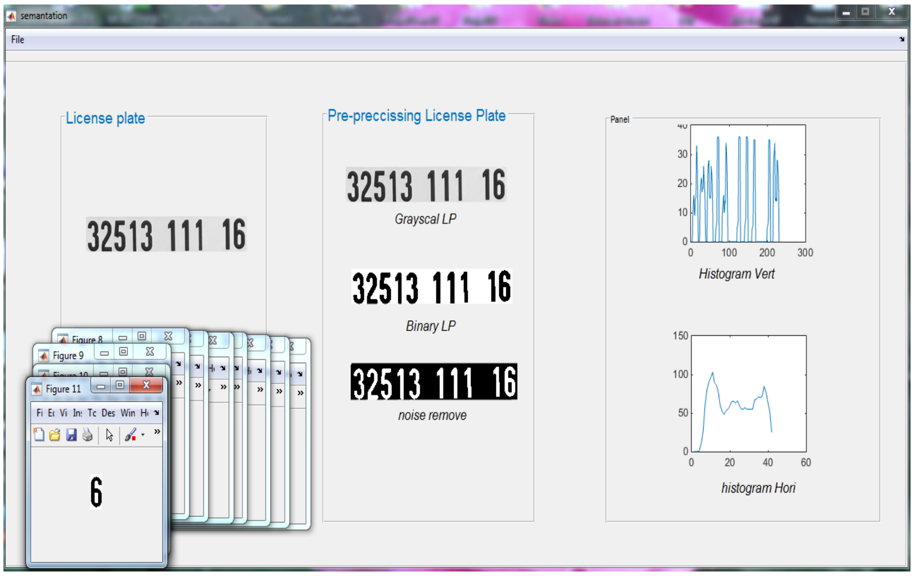


Figure 4.29interface of character gementation step.

4.7 Conclusion

We have presented in this chapter the development environment and give a detailed description of our license plate recognition system with the performance evaluation of each phase of the recognition process. We also presented the experiments results by using classifiers based SVM and based KNN.

Our system has produced acceptable results in terms of recognition: for the binaire digit data base, we have found that the Hu Invariant Moments method gives the best recognition rate of 80% using SVM.

Bibliographie

[1] wikipedia, www.wikipedia.com, Vehicle registration plate - Wikipedia, the free encyclopedia25/03/2016.

[2] https://www.primoregistrations.co.uk/article/view/number-plates-around-the-world-africa-and-asia.

[3] http://www.worldlicenseplates.com/world/AF_ALGE.html.

[4] H. Ferroudj, License plate recognition, Master, University Mohamed Khider – BISKRA, 2015.

[5] Y. P. Huang, C. H. Chen, Y. T. Chang, and F. E. Sandnes, An intelligent strategy for checking the annual inspection status of motorcycles based on license plate recognition, Expert Syst. Appl., vol. 36, no. 5, pp. 9260– 9267, Jul. 2009.

[6] C. Anagnostopoulos, I. Anagnostopoulos, V. Loumos, and E. Kayafas, A license plate-recognition algorithm for intelligent transportation system applications,IEEE Trans. Intell. Transp. Syst., vol. 7, no. 3, pp. 377–392, Sep. 2006.

[7] V. Shapiro, G. Gluhchev, and D. Dimov, Towards a multinational car license plate recognition system, Mach. Vis. Appl., vol. 17, no. 3, pp. 173– 183, Aug. 2006.

[8] Ondrej Martinsky, Algorithmic and Mathematical Principles of Automatic Number Plate Recognition Systems, BRNO University of Technology, Faculty of Information Technology, Department of Intelligent Systems, pp.8-22.

[9] Gary Bradski and Adrian Kaehler ,Learning OpenCV,O'Reilly Publication, September 2008, pp.16-80.

[10] D.H. Ballard, Generalizing the Hough Transform to Detect Arbitary Shapes, Pattern Recognition, vol. 13, no. 2, pp. 111-122, 1981.

[11] S. L. Chang, L. S. Chen, Y. C. Chung, and S.W. Chen, Automatic license plate recognition, IEEE Trans. Intell. Transp. Syst., vol. 5, no. 1, pp. 42– 52, Mar. 2004.

[12] Christos Nikolaos E. Anagnostopoulos, Ioannis E. Anagnostopoulos, Vassili Loumos, and Eleftherios Kayafas, A License Plate-Recognition Algorithm for Intelligent Transportation System Applications, pp. 377-392, 2006.

[13] Rinku solanki, Naitik kapadia, Viral patel, the review on automatic license plate recognition, International Journal of Research in Engineering and Technology,vol 02, pp 178,2013.

[14] Chirag Patel, Dipti Shah, Atul Patel, Automatic Number Plate Recognition System (ANPR): A Survey, International Journal of Computer Applications (0975 – 8887), Volume 69– No.9, May 2013

[15] Nuzulha Khilwani Ibrahim, Mohamad Riduwan, License Plate Recognition (LPR): A Review with Experiments for Malaysia Case Study, The International Journal of Soft Computing and Software Engineering, Vol. 3, 2013.

[16] Y.Wen, Y.Lu, J.Yan, Z.Zhou, K.M.von Deneen, and P.Shi, An Algorithm for license Plate Recognition Applied to intelligent Transportation system,IEEE Trans.Intell.Transp.Syst., vol. 12, no.3, pp. 830-845, Sept- 2011

[17] S. Chang, L. Chen, Y. Chung Chung and Sei-Wan Chen, Automatic License Plate Recognition, IEEE Transactions on Intelligent Transportation Systems, VOL. 5, pp.1524-9050, March 2004.

[18] Christos Nikolaos E. Anagnostopoulos, A License Plate Recognition Algorithm for Intelligent Transportation System Applications, IEEE Transactions on Intelligent Transportation Systems, Vol. 7, pp. 1524-9050, September 2006.

[19] SerkanOzbay and Ergun Ercelebi, Automatic Vehicle Identification by Plate Recognition, International Journal of Electrical, Computer, Electronics and Communication Engineering, Vol. 1, 2007.

[20] C. Nikolas E. Anagnostopoulos, License Plate Recognition from Still Images and Video Sequences: A Survey, IEEE Transactions on Intelligent Transportation System, VOL. 9, pp. 1524-9050, September 2008.

[21] C. Nelson KennadyBabu, Siva Subramanian T and Kumar Parasuraman, A Feature Based Approach for License Plate Recognition of Indian Number Plates, pp. 4244-5967, IEEE, 2010.

[22] H.E. Kocera and K. K. Cevikb, Artificial neural networks based vehicle license plate recognition, SCIENCE DIRECTProcedia Computer Science, pp. 033–1037, 2011.

[23] Ying Wen, Yue Lu, An Algorithm for License Plate Recognition Applied to Intelligent Transportation System, IEEE Transactions on Intelligent Transportation Systems, VOL. 12, NO. 3, pp. 830-845 September 2011

[24] S. Kranthi, K. Pranathi, A. Srisaila, Automatic Number Plate Recognition, International Journal of Advancements in Technology, Vol. No. 2, No 3, July 2011.

[25] Rupali Kate, Number Plate Recognition Using Segmentation, International Journal of Engineering Research & Technology (IJERT), Vol. 1, ISSN: 2278-0181, Issue 9, November 2012.

[26] C. Chunyu, W. Fucheng, C. Baozhi, C. Xin and Z. Chen , Application of image processing to the vehicle license plate recognition, Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE), 2013.

[27] Shan Du, Automatic License Plate Recognition (ALPR): A State-of-the-Art Review, IEEE Transactions on circuits and Systems for video Technology, VOL. 23, NO. 2, February 2013.

[28] J. K. Chang, S. Ryoo, Heuiseok Lim, Real-time vehicle tracking mechanism with license Plate recognition from road images, Springer Science Business Media, pp. 353-364, 2013.

[29] Wei Xie and Y. Wu, License Plate Automatic Recognition System Based on MATLAB-GUI, The Open Automation and Control Systems Journal, pp. 497-502, 2014.

[30] H. Kaur, N. Kumar Garg, Indian Number Plate Recognition and Segmentation Using K Mean and Neural Network Classifier, International Journal of Advances in Computer Science and Communication Engineering (IJACSCE), Vol. 2, Issue2, June 2014.

[31] P. Prabhakar and P. Anupama,A Novel Design for Vehicle License Plate Detection and Recognition, IEEE 2nd International Conference on Current Trends in Engineering and Technology, Conference Number – 33344 July, 2014

[32] N.Marref , apprentissage incrémental & machines à vecteurs supports, magister, université hadj lakhdar – batna,2013

[33] N. Ayat, Sélection de modèle automatique des machines à vecteurs de support , application à la reconnaissance d'images de chiffres manuscrits. Thèse présentée à l'école de technologie supérieure, Montréal, Canada, 2004

[34] https://en.wikipedia.org/wiki/Sobel_operator,12/05/2016.

[35] https://en.wikipedia.org/wiki/Otsu%27s_method 12/05/2016.