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# An Intelligent Character Classification Method for Automatic License Plate Recognition

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**Abstract**

*The purpose of this paper is to introduce a robust method to address the problem of license plate recognition on the basis of an illumination compensation technique and intelligent character recognition algorithm. To foster our aim, we firstly frame the input video from into stream of images the database. We then apply our pre-processing and local normalization algorithms to remove the noise and variance of lighting conditions. The image registration is utilized for the plate segmentation and feature construction. The improved cross correlation and D-Isomap [5] analysis are used separately for final stage in character recognition. The experimental results demonstrate a significant performance improvement achieved by the proposed methods*

**Keywords:** Intelligent Character Recognition, Isomap, Plate Segmentation.



## Introduction

Vehicle’s license plate recognition system has been a special area of interest in video surveillance arena for more than a decade or so. With the advent of sophisticated video vehicle detection systems for traffic management applications, number plate recognition system finds wide varieties of places to fit itself beyond just controlling access to a toll collection point or parking lot. It can now be integrated to the video vehicle detection systems which usually are installed in places of interest for intersection control, traffic monitoring etc., to identify vehicle that violates traffic laws or to find stolen vehicles. There are a number of techniques used so far for recognition of number plates such as BAM (Bi-directional Associative Memories) neural network character recognition [1], pattern matching [2] etc.

Automatic license plate recognition (LPR) is A process that may utilize automatic text extraction methods in order to extract plate numbers from images or videos containing vehicle's license plate. LPR is utilized to ease the identification of vehicles through their license plates. Wherever traffic management and security control for vehicles is required, automatic LPR plays an important role. By installing monitoring cameras in parking lots, highways, and intersections, and utilizing LPR systems, violator drivers, lost or stolen cars can be recognized from video images of the license plates. For example automated speed enforcement detects speeding drivers using LPR systems. After the system captured the speeding car and their license plate number extracted and recorded, corresponding authority will be informed about this.

However the current control systems are manually capable of remote traffic control by operators who can pan, tilt and zoom the cameras from the Traffic Control Centre to monitor the traffic and continually adjust signal timing to alleviate congestion and reduce delays, the task of automatically acquiring license plate from video images for automatic recognition of traffic violators is still under research. Furthermore, even though many contributions have been made for automatic plate recognition, there is still no standard methodology. Extracting plate number automatically is extremely difficult due to various problems.

These problems may include from difficulty in finding the best image of vehicle in temporal models and searching for plates in the frames, to variety in image orientation, alignment, in addition to low image contrast and complex background. While a large number of techniques have been proposed for character recognition, only a few have used video sequences and the rest have used databases including only images. Another problem is while segmentation of characters is usually done with much ease manually, it is difficult to be done automatically. Furthermore at the stage of templates comparison for character recognition, Template Matching is usually evaluated using the square distance or the cross correlation [3]. However, these methods are not usually robust since they need heavy computation by the processor.

Since representation of characters, symbols, and texture may vary from one plate to another, LPR has recently become country or even province dependable. For example, countries such as Argentina, India, and Iran have focused their research on country dependable

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license plate recognition. So we have chosen to present a province dependable methodology for LPR. Another advantage of our method is that we have detected license plate automatically under different of lighting conditions. To be prepared for recognition, the segmented characters of license plates are normalized based on local normalization. In order to obtain better accuracy and robustness, in the present method we propose the cross correlation and Discriminative-Isomap (D-Isomap) for the final decision.

## Related Work

Recognition algorithms reported in previous research are generally composed of several processing steps, such as extraction of a license plate region, segmentation of characters from the plate, and recognition of each character. Papers that follow this three-step framework are covered according to their major contribution in this section. The major goal of this section is to provide a brief reference source for the researchers involved in license plate identification and recognition, regardless of particular application areas (i.e., billing, traffic surveillance etc.).

LPR involve issues that matter a great deal to researchers as they seek to develop the most robust and fastest system of recognition. The research may be dedicated to one aspect of LPR, such as research on license plate localization, or segmentation of characters [6]. However a complete and successful license plate recognition system is a challenging process that includes some pre-processing, license plate localization, template matching and finally recognizing the characters in the plate and applying Optical character recognition (OCR) to convert the characters to text and save them in a file. Approaches that have been proposed in pre-processing to handle the illumination problem include: illumination insensitive representations, modelling of illumination variations and illumination normalization to a canonical form. Examples of this technology include: Tan and Triggs' [7] system working under uncontrolled lighting based on robust pre- processing and an extension of the local binary pattern (LBP) local texture descriptor. Another research [8] used spherical harmonic representation to explain the low dimensionality of images under different illumination conditions. Li et al. [8] presented a method for indoor, cooperative-user applications, including active near infrared (NIR) imaging hardware, algorithms, and system design, to overcome the problem of illumination variation: an illumination invariant face representation is obtained by extracting LBP features from NIR images.

After illumination compensation one of the greatest challenges in LPR is spotting the region where characters are placed. Some approach in literature of character segmentation does not even attempt to isolate each character in the plate and instead, template matching is applied directly on the whole plate image [9]. Common techniques to detect the character regions in a plate localized input image include, edge detection, mathematical morphology, Connected Components Analysis, genetic algorithms and lateral histogram analysis.

After localization the broad issues of character extraction is necessary for researchers to investigate. To recognize each character, several machine learning and non-machine learning algorithms have been employed in related papers. Feed- Forward Neural Networks, networks trained by the BRLS learning algorithm, Self-Organizing Maps, Probabilistic Neural Networks and Enhanced Neural Networks, are some of the machine learning based algorithms that have been applied. Non-machine learning methods include critical point extraction, and template matching.

Isomap is an isometric feature mapping that was first proposed by Tenenbaum, and is capable of dealing with curse of dimensionality. First, in Isomap based methodology nonlinear dimensionality reduction has warrant. It well justifies to learn complex embedding manifolds within a single global system under local geometric metrics. Second, by using geodesic distances instead of Euclidean distances, the manifold structure of the input space will be encoded to distances, i.e. a sparse graph in which each node is connected only to its closest neighbours is constructed and the geodesic distance between each pair of nodes is taken to be the length of the shortest path in the graph that connects them.

Yang proposed the Extended Isomap (EI) [10] for a face recognition, which was utilized by a Fisher Linear Discriminant (FLD) algorithm. In another work by X. Geng an improved version of Isomap [7] is proposed in which neighbourhood graph of the input data is constructed according to a certain kind of dissimilarity between data points. It is specially designated to integrate the class information. In this paper we propose a D-Isomap based method to solve the LPR problem [11].

## Proposed System

This work consists of six steps and the performance of license plate localization is crucial for the entire system, since it directly influences the accuracy and efficiency of the subsequent steps. We heavily focus on the incorporation of local normalization with Optimal Adaptive Correlation (OAC) [4] technique to automatically detect the license plate on video sequences. As the first part of the process, each frame of the input video sequences is extracted and processed through illumination compensation. Then license plate candidate regions are roughly located, which has been achieved through candidate selection by OAC. After license plate localization the segmentation is applied utilizing an edge detection methodology. Finally in character identification section the procedural limitations of frame based classifiers are outlined and video based experiments are applied. The six stages of this process are shown in Figure 1 and can be defined as follows.

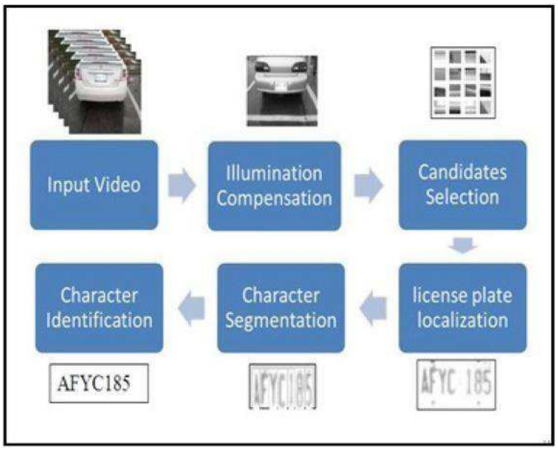


**Figure 1.** General structure of LPR system

A. Illumination compensation

The problem of brightness variation is possible to be generally corrected by normalizing to a given intensity level, which includes gamma intensity correction (GIC), difference of Gaussian (DoG), local histogram matching (LHM) and local normal distribution (LND). In GIC the goal is to achieve as close as possible to a canonically illuminated image, compensating pixel values of the image by exponentiation. The resulting, which is obtained by transforming the input image pixel by pixel over its position is a function of optimal Gamma coefficient. The DoG filter is then applied for removing the intensity gradients from the image. LHM integrates the information to the global histogram distribution. Assuming the gray values drawn from a normal distribution, LND is then applied for the normalized output image.

B. Candidate selection and License plate localization

As we proceed further in the process, to locate the license plate candidate, OAC on the normalized images is considered. An advantage of using OAC algorithm is that the pyramid of downscaled copies of the input images does not need to be used and thus gives a high overall pace to the process.

C. Character segmentation

Basically, the algorithm of the license plate location plays a key role in this system. In order to extract the license plate more accurately, we decide to implement the algorithm for the binary image. After the image pre-processing, we obtained an appropriate binary image. According to the analysis for the feature of the license plate, typically, the white pixels should be correlated with a license plate. However, there are some interference factors to interfere reorganization, such as logo of the car and so on. Therefore, applying the length-width ratio for license plate which we have been set, we could extract the license plate correctly.

In this algorithm, we should treat the binary image as a matrix. As we know, when extracting the rectangle, we should know the 4 points coordinates to limit the field. Therefore, we divide this algorithm into two steps. First step is to find the two y-coordinates and the second is to find the x-coordinates.

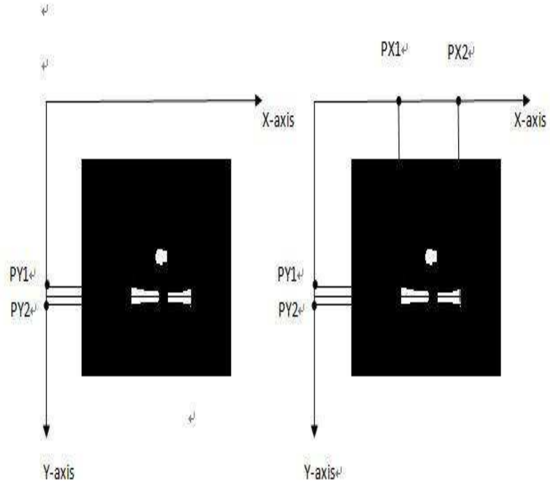


**Figure 2.** (a) It displays the first step of this algorithm. (b) It shows the second step of the algorithm.

(a) In this step, we find the white pixels and accumulate the pixel values in each row. For every y-coordinate, there is a corresponding sum value. We should find the maximum sum value and record the corresponding y-coordinate to PY1 and PY2. Next, we search up and down along the vertical direction for finding the terminated coordinate which can be treated as the edge of the license plate. Therefore, using a loop to look up alone y-axis until the sum of some row's pixel values reduced to less than 5, PY1 was recorded and look down until the sum of some row's pixel values reduced to less than 5,PY2 represent the another termination value(Figure 1(a). So far, we have obtained two y-coordinate (PY1and PY2) to limit some filed.

(b) In this step, our purpose is to find the two *X*-coordinates which we call *P_X1* and *P_X2*. After the previous step, we obtained a region which is limited by *PY1* and *Py2*. On this basis, we could do some operation to extract the license plate. We create a loop to find the *PX1* and *PX2* firstly. The idea of finding them is similar with the previous step which is to calculate the sum of pixel values in each column. We could obtain the PX1 and Px2 along the horizontal direction. So far, the four coordinates which are PY2, PY1, PX1, and PX2 could define a rectangle; see Figure 2(b). Actually, this rectangle represents the license plate.

**Adjust license plates which are in the different angle**

There may be some parts of license plate that are disappearing if this plate is at certain different angle to the observer. Firstly, the cutting range should be increase in cutting process, because both of the length and width from the oblique plate are longer than that of horizontal plate according to mathematic. In the Figure 2 (a), we assume that *L* is the length and *W* is the width of license plate. If the license plate is the different angle to the observer, such as Figure 2 (b), the width is *W1 (W1>W)* at least in the area we need to cut from the original image.

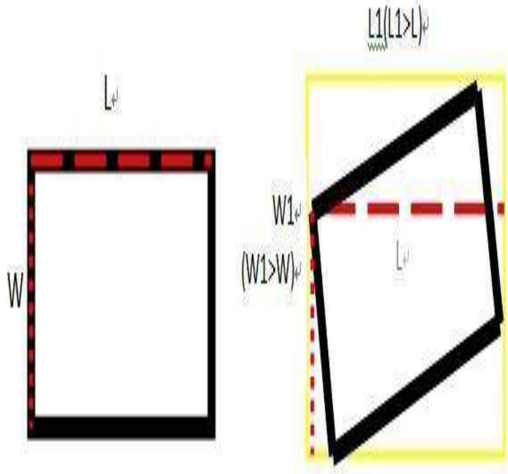


**Figure 3:** The principle of mathematic

After that, the radon transform is used to find out the angle between the license plate and horizon. Before we use the radon transform to adjust license plate, we test the basic function of radon transform. A simple image which is similar to license plate is created, and we work it in radon transform at 0, 45, 90 degrees separately. *[R, xt] = radon(I, [0 45 90]);*

In this processing, the edge detection should be done firstly. During the test, the result of the canny detection is better than others ways. Then, according this principle, we search for the angle between license plate and horizon. In other word, we need to find out which angle the license plate is projected in mostly. At last, the maximal angle we should find out and save it. Next, the function re-rotate is used to adjust the license plate to the horizontal direction depending on the angle.

**Extract the license plate in more advanced detailing**

Before segmenting the license plate, some basic pre-process is still necessary. Because we expect to obtain a relatively perfect binary image for the operation. So far, we have already extracted a license plate with its angle adjusted. Next, we would remove some interference which is the stuff except the characters.

Firstly, we convert the grayscale image to a binary image. The output image replaces all pixels in the input image with luminance greater than a threshold value with the value 1 (white) and replaces all other pixels with the value 0 (black). We used the function to compute the threshold value argument.

Secondly, in order to optimize the image, we should apply some morphological operations to the binary image. One of the morphological operations is represented by a function which removes the H-connected pixels. Another morphological operation is applied by a function. It removes the spur pixels. At last, in order to remove small objects, we would morphologically open binary image. This function removes from a binary image all connected components (objects) that have fewer than some pixels, producing another binary image. So far, we could obtain the license plate. However, the black border is also still exist. Therefore, in next step we would establish a function to remove the black border. The idea of creating this function has a little similarity with the idea of license plate location. If we can find the four coordinates, the rectangle which just contains the characters and EU symbols would be extracted. To this goal, we search up and down the y- coordinate from the have of the size in the vertical direction. There is a value to determine whether the loop should continue or terminate. After huge numbers of the experiments, we find that using a function to find the average value to be the threshold is appropriate.

Typically, as for the two X-coordinates, we make them 1 and x respectively. Therefore, we could extract the image by four coordinates. Actually, some interference factors outside the license plate have so far been removed. However, some noise in the license plate has not yet been removed. Therefore, the morphological operation is necessary again Segment the characters out from license plate.

The character segmentation is a significant part in this system. We establish a function to segment the character.

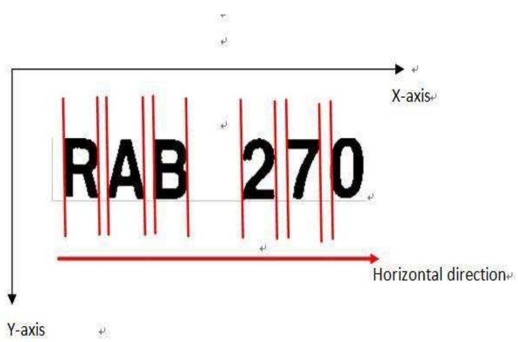


**Figure 4.** character segmentation

At the beginning, we make this matrix oppositely. Then, we use the sum function which is to return the row vector of the sums of each column. Next, we should research matrix along the horizontal direction by a loop. According to the sum, we could create the limited condition to judge whether the loop continue or terminate. The limited condition is when the sum of some column is less than 1 and the sum of next column is greater than 1, then it will be segmented from this column to before. Certainly, if the condition isn't satisfied, it would continue to search. If the car is belonging to Europe Union, the characters added one logo is 7 blocks. Therefore, it need segment 14 times in total. Otherwise, it just needs 12 times segmentation. In the processing of segmentation, we set a counter to calculate how much segmentation the programming need to segment.

**D. Character Identification**

Cross correlation is considered as a generally signal matching, computationally expensive method and used in image registration. The process of cross correlation based classification is shown in Figure. This method gives the numerical value of similarity between the character and its matching template and is classically defined with the bellow formulation

$$r = \frac{\sum_m \sum_n \left(A_{mn} - \bar{A}\right)\left(B_{mn} - \bar{B}\right)}{\sqrt{\left(\sum_m \sum_n \left(A_{mn} - \bar{A}\right)^2\right)\left(\sum_m \sum_n \left(B_{mn} - \bar{B}\right)^2\right)}}$$

Given a segmented (isolated) character and the templates, which are defined as cell structure of fixed pixels for 26 elements of letters and 10 elements of numbers, by cross correlation the matching character can be easily extracted. It compares feature vectors to the various models and finds the closest match. One can use a distance measure. Each character can be considered as a pdf in the feature space. The 2-D moments of the character are shown in the following equation

$$m_{pq} = \sum_{x=0}^{W-1} \sum_{y=0}^{H-1} x^p y^q f(x, y)$$

From the moments we can compute features using: a. Total mass (number of pixels in a binarized character), b. Centroid (Center of mass), c. Elliptical parameters - Eccentricity (ratio of major to minor axis), Orientation (angle of major axis), d. Skewness, and e. Kurtosis. Given labeled sets of features for many characters, where the labels correspond to the particular classes that the characters belong to, we wish to estimate a statistical model for each character class.

B. D-Isomap based approach

The D-Isomap based method is used for the final recognition. It has three steps: Construct neighbourhood graph. Compute shortest paths. Construct d-dimensional embedding. In construct neighbourhood graph step. a point is a neighbour of any other point if it lies within a fixed radius Q or is one of the K closest points to it. The neighbourhood graph is constructed with edges equal to the distance between the points. In the step of compute shortest paths, the geodesic distance between all points is calculated by computing the shortest paths in the neighbourhood graph. Classical MDS is applied in the last step to obtain a low dimensional embedding of the data. This method provides a simple solution to obtain the low dimensional embedding and discovers the discriminative structures on the manifolds. It has the capability of discovering the nonlinear degrees of freedom and finding globally optimal solutions guaranteed to converge for each manifold. Final decision is made using a Nearest Class Center (NCC) algorithm to determine the emotion classes. Unlike other alternatives such as EM or nearest-neighbours algorithms, NCC considers the centers for the clusters k with known label from the training data and generalizes the class center for each emotion group. The derived cluster centers have more variations than the original input features and thus expands the capacity of the available data sets. The classification for the test data is based on the nearest distance to each class center.

**Experimental Result**

In order to evaluate the performance and robustness of the proposed algorithm against the disturbances such as: the in exact image of the license plate frame, the plate colour and the non-uniform illumination, we used a dataset that consists of videos available on the Web and videos recoded by ourselves. All samples are running at 30 frames per second on images of 320x240 resolutions. Videos in this dataset contain Ontario license plates at different sizes, lighting conditions and poses, and at various positions. Figure 5 shows some samples from this dataset. The experiments were implemented on a Quad CPU 2.4GHz PC with 3.25 GB memory, under the Windows XP operating system.

**Figure 5.** Samples of Ontario license plates from the dataset

A. Normalization Results

To ensure that lighting variants would not affect the outcome of the plate recognition, the pre-processing step is applied for the input video sequence. By the illumination compensation, it shows that the histograms of all input frames are widely spread to cover the entire gray scale, and the distribution of pixels is not too far from uniform. Examples of the filtered results of the original images are shown in Figure 6. As a result, dark images, bright images, and low contrast images are much enhanced to have an appearance of high contrast.

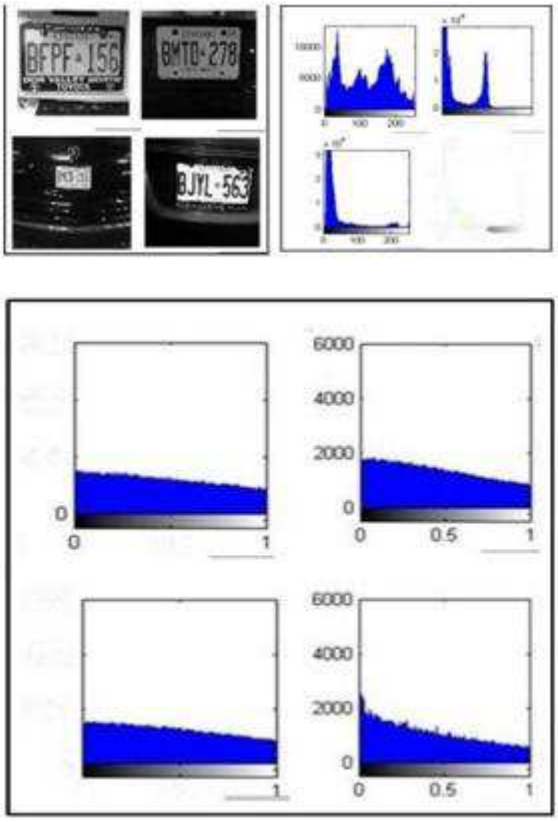

Figure 6 Samples of filtered normalization results

B. Character Recognition

In this section several experiments were performed to evaluate our proposed methods for LPR using the above mentioned dataset. Figure is the results of correlation between each character with the entire templates. The value of the correlation for each character is maximized, whenever it matches to its template. The horizontal axis is the index of each character and the vertical axis is the index of templates. The linearity of the graph depicts that correlation is successful in character classification and its accuracy is about 72%. As Figure above also shows, the D-Isomap based method has a higher recognition rate. The accuracy of this method is about 91 %.

## Conclusion

This paper has proposed a character recognition algorithm in order to perform the LPR. However, character recognition has extensive applications rather than LPR. It is widely used as a form of data entry from some sort of original paper data source, whether documents, sales receipts, mail, or any number of printed records. It is crucial to the computerization of printed texts so that they can be electronically searched, stored more compactly, displayed on-line, and used in machine processes such as machine translation, .text-to-speech and .textrning. The proposed method of number-plate characters recognition uses coloration to classify the extended futures. This method is based on template matching and is in order to improve recognition rate and reduce recognition time.

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