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Vehicle Number Plate Identification Using a Bi-Step Region Segmentation and Classification Technique

Raja Mursleen Bhat[1], Ravinder Pal Singh[2], Jasmeen Gill[3], and Dr. Monika Mehra[4]

[1]Research Scholar, Department of Research, Innovations and Incubation, RIMT University, Punjab, India
[2]Technical Head-Department of Research, Innovations and Incubation, RIMT University, Punjab, India
[3]Research Associate, Department of Research, Innovations and Incubation, RIMT University, Punjab, India
[4]Head, Department of Electronics and Communication Engineering, RIMT University, Punjab, India

Correspondence should be addressed to Raja Mursleen Bhat; rajamursleen4@gmail.com

ABSTRACT- Vehicle number plate identification (VNPI) is an imperative task for resolving the increasing traffic issues around the world. Although many studies were conducted in the past, there are still many challenges to be answered where noisy image acquisition conditions, improper illumination or poor quality images, are a few to name. In the light of the same, an efficient vehicle number plate classification model is the need of the hour. Since, image processing techniques are best suited for resolving the problems of noisy dataset; these are used for noise elimination, image segmentation, feature extraction, and classification purposes in this research. So, in this article, a two-step approach, using region based segmentation and feature extraction to feed as input to the system for classifying the vehicle number plates, has been designed. The proposed bi-step VNPI model very well extracted the segments around the characters with extraction rate of 96.69% and recognition rate of 95.34%. Experimental results show that the proposed technique is simple and robust. The results are comparable with the results of the state-of-art methods available in the literature.

KEYWORDS- Vehicle number plate identification; region-based segmentation; noise elimination; alpha-numerals; pattern recognition

I. INTRODUCTION

Traffic monitoring is one of the major challenges faced by the nations across the globe. With the rise in the number of vehicles on roads every year, the problem has even worsened. Increasing the number of automobiles requires more efficient ways of road traffic management and therefore, one chief reason that is 'safety' mandates the employment of advanced vehicle control and monitoring methods. Furthermore, recognition of vehicles is quite significant to implement an effective traffic monitoring system.

Keeping this perspective in view, many way outs have been employed. However, in the present scenario, monitoring is performed through video recording of vehicles on roads and in parallel, some staff is being employed for scanning the screen and tracking the vehicle. This task is more or less manual due to high degree of human intervention. Manual vehicle recording is a time-consuming, labor intensive, expensive and inefficient task. As a result, an efficient automated system is required to recognize the vehicles through their respective number plate registered. The automated vehicle plate identification offers a number of benefits over the manual systems such as speeding-up the procedures, minimal human intervention, cost effective and accurate; thus, such systems are required (Gill and Singh 2022). In this chapter an overview of Automated Vehicle Number Plate Identification system, its applications in real world along with its components and limitations of existing models have been presented.

The remaining article is organized as follows: a brief literature survey is provided in Section 2, details of proposed model and methodology are given in Section 3, results and discussions are presented in Section 4, and the conclusions are summarized in Section 5.

II. LITERATURE REVIEW

Endeavors in the field of Vehicle Number Plate Identification have been put from early 1990s. Lotufo et al. (1990) proposed a novel vehicle tracking and recognition system employing image processing techniques; Resulted in an extraction rate of 95% and a classification rate of 80% in matching the features. Kanayana et al. (1991), however, studied the effect of daylight and proposed a VNPI system working with an accuracy of 90% in daylight and 60% during nights. Likewise, to find edges in the image of a car, Sarfraz et al. (2003) suggested VNPI using the Sobel filter with a success rate of 95%. Another effort was done by Chang et al. (2004) who proposed a novel model to segment and identify the number plates based on neuro-fuzzy classifier.

To locate and extract number plates from complicated sceneries, Rattanatgannawat et al. (2006) suggested a new edge-based automobile plate detection technique. The technique was evaluated by the authors using actual CCTV camera recordings with 94% accuracy. Similarly Khan et al. in 2007, developed an innovative method for automatic car plate recognition in which no restrictions on distance, color, or a single plate were applied. The suggested algorithm is effective in addition to being faster.

Another attempt specifically, for Indian naming conventions, was done by Parasuraman et al. (2010). The algorithm was validated through real time Indian number plate vehicle images acquired under varying circumstances and yielded satisfactory results thereof.

Yet another classification model was proposed by Fikriye et al. (2012) to identify the plates in various lighting conditions. The authors pre-processed the data using the Otsu Thresholding algorithm, segmented the characters using a Column Sum Vector, and recognized the characters using a probabilistic neural network. With this algorithm, each plate could be recognized in an average of 0.1 seconds. This algorithm reached a recognition percentage of 96.5%.

It is reported that the VNPI process accomplishes in four main phases. The first phase is to record video and images of the vehicle using a camera. After converting the video to frames, key frames are selected for further reference. Images may contain impurities such as holes and dirt particles. Noise is removed from the vehicle images in the preprocessing stage. In the literature, median, Gaussian, and Mexican hat filters are often used to remove noise from disks. Gaussian filters perform better than median filters in high noise image processing (Muzammil et al., 2013).

In the number plate detection step, the vehicle number is extracted from the preprocessed vehicle image. Vehicle license plate features such as, aspect ratio, color, size and rectangular shape are used to locate the number plates. Several methods such as Principal Component Analysis, Artificial Neural Networks, Decision trees, Support Vector Machines, Image Processing methods and Morphological operations have been implemented for number plate detection. In order to segment the characters from the number plates, various segmentation techniques have been employed in the past studies, for instance, threshold-based segmentation, region-based segmentation, intensity based segmentation, Otsu segmentation, edge based segmentation, to name a few. For the purpose of improved quality for correct image segments, different techniques are hybridized together.

Anagnostopoulos et al. (2008) found the fact that dust, poor illumination images, darkness, and physical damage may decrease the efficiency of segmentation of alpha-numerals on number plates. Finally, the main task is to recognize the alphanumeric characters present on the vehicle plate.

Despite the extensive literature and research available on VNPI, the field has not progressed beyond basic technology. In real time scenarios, there are numerous challenges to be met for instance poor illumination conditions, presence and absence of sunlight, poor weather conditions, glared images, blurriness in images due to vehicle movement, and many more. Perhaps, this could be a possible reason for availability of very few contributions related to model that can work in all or multi-environment conditions. Therefore, an efficient and accurate license plate recognition model is the need of the hour and thus, got the motivation of the present system to reach a high level of detection and identification rate.

III. MATERIALS AND METHODS

The most imperative task in automated number plate identification is the input being fed to the system. The inputs can be of two types: image-based data or video based data. Image based data requires on-site image clicking, that is data in the form of images are to be acquired from moving vehicles and simultaneously fed to the VNPI system as input. The major components of VNPI system are shown in Figure 1.

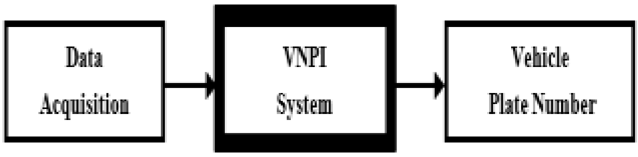

Figure 1: Components of VNPI System

Whereas, video data are collected through a two-step process- firstly, videos are recorded with the help of a video camera for the vehicles which are moving and thereafter, converted to frames for feeding into the VNPI system for processing. Clicking the images of moving objects in real time environment is undoubtedly a challenging task since quality of images may not be good. However, in case of video capturing, the video once recorded can be converted later on into 'frames' and then passed to VNPI system. This, in fact, gives better processing and hence higher accuracy rates than the on-site image clicking.

The hybrid fruit grading model comprised of five major phases: Image acquisition, pre-processing, segmentation, feature extraction and classification, as shown in figure 1.

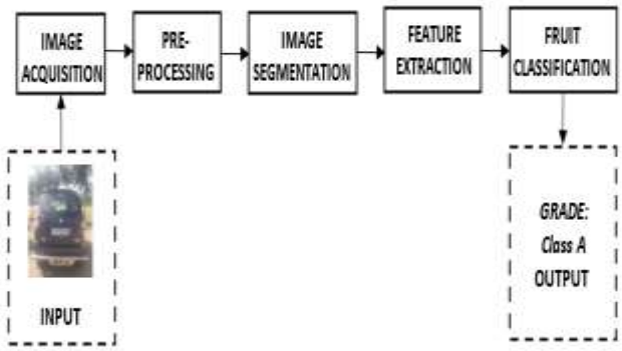

Figure 2: Block Diagram of Vehicle Number Plate Identification Model

A. Image Acquisition

The model initiated with the image acquisition task. The primary task in video based VNPI is recording the video of a position changing automobile employing a digital camera. Thereafter frames are developed and most significant frames are chosen for further processing and stored in the memory to feed as input to the VNPI system. The reason for not processing all the frames is that discarding the frames that will least contribute to the classification process is necessary, or if kept, unnecessary computations have to be performed, thereby making the system more complex.

Own camera set-up was used to record the vehicle in motion. A Nikon video camera was used for recording the images. Afterwards, a database of 500 frames of images was prepared to store the number plates for further use.

B. Pre-processing

The next task after image acquisition was the resizing and cropping of images to a fixed size. All the images were resized to same dimensions of 100×100.

The process of VNPI is not much challenging but doing the same with accuracy is quite challenging. During acquisition of images, dataset may not be in the form ready for identification. It has many kinds of noise viz. blurriness due to moving objects, low quality/dark images because of inappropriate or no sunlight, too much bright images due to excessive daylight that is glare on the vehicle surface. As a result, images are pre-processed first, by eliminating the noise to improvise their quality, and make these in a form ready for classification.

The task of noise elimination or image enhancement are accomplished using filter-based techniques, and contrast or brightness are reset if required. So, the images were enhanced using Wiener filter. The reason for using Wiener filter was that it adjusts itself according to the local intensity variance in the image. The filter performed less smoothing for regions of large intensity variance and more smoothing for regions of small variance values. Therefore, the filter was very well suited for applications where fruit edges were to be retained while small bruises on the surface were to be smoothed off.

C. Segmentation

After pre-processing the vehicle images, there comes another important task that is image character segmentation. This is basically a two-step process. Here, alpha-numerals from the license plate are segmented from the enhanced, noiseless automobile images in the dataset. The background details are subtracted from the images to shed off the unnecessary details thereby avoiding unnecessary computations.

Moreover, background details may interfere in the classification of the region of interest leading to inaccurate results. Here the digits or alphabets present on the number plates are further segmented from each other so as to obtain single letter/digit to feed to feature extraction phase. This is done automatically by drawing a kind of bounding box around the alpha-numerals and enclosing them inside it. The steps of the algorithm are given in figure 3.

D. Feature Extraction

Input to the system is always given in the form of values computed from the images and not the images directly fed to the classification phase. For this purpose, features are extracted from the segmented alpha-numeral images of automobiles. The feature set includes shape based, color based, size based and location-based features for instance, area, perimeter, major axis, minor axis, orientation, contours, closed areas, curves, bounding box, corners, shape, rectangularity, circularity, etc.

```
-----------------------------------------------------------------------------------
Algorithm 1: Vehicle Number Plate Character
Segmentation Technique Input: Image of Vehicle
Output: Registration number of vehicle written on license number plate
-----------------------------------------------------------------------------------
Procedure VNPI
Begin
Input image as I
I← pre-process (I);
Extract region of I as R where R is a set of subregions
        R := {rn, rn, rn, ... rr-}, 1 ≤ i ≤ n
for each region ri
        gi ← make-group ( ri ) end for
G is a group as {gn, gn, ... g }, m ≤= n
If m > t/m
            R← filter regions(R)
            Go to step 4;
        End if
If m < t/m
            R← regroup region(R) Go to step 4
```

Figure 3: Steps of Region Segmentation

E. Classification

Last but not the least step is classification step where the alpha-numerals are actually identified and the important task for what the whole process has been done. Template matching has been performed for classification. The identification of identical regions on the basis of their similarity and dissimilarity measure for region extraction. Thereafter, correlation of the neighboring pixels is computed to find out the similarity between the regions.

Dataset consisting of images of vehicles is divided into two parts. One part of the dataset is used to train the proposed system and another part is used to test the system.

Characters are recognized for both trained data and test data. The correlation technique for each extracted character is used to match the characters from the trained dataset. Classification is performed using the comparison of extracted character with a set of similar template images. After all the templates have been compared with the extracted character, the most similar template is the recognized character. The geometric properties of the character are used to find a perfect match.

IV. RESULTS AND DISCUSSION

The multi-fold cross-validation is employed for testing the proposed algorithm. In cross-validation, the dataset is divided into two subsets. A particular sub-set of the database is used for training the system and is called trained data. Another sub set is used to test the system and is called test data. The experimentations are performed on different partitions of the dataset. As the correlation technique is used, results are noted for both trained and test datasets. The main focus is on correct regions identification as the first step of this study. The results are presented for all correct character regions recognized in number plate, all correct recognized except one and all correct recognized except two.

The developed system is applied successfully and it could be helpful to use in other real-life applications. The sections 4.1 to 4.4 summarize the experimental results for different folds of the dataset.

A. Results for Fold 1 (Trained Images =300, Test Images=200)

In fold 1, 300 images are taken in training set and 200 images are taken in test set randomly. The proposed system is trained for 300 vehicle images and tested on 200 vehicle images. The character region extraction results are summarized in Table 1 and Figure 4. The character extraction regions accuracy for train datasets are 97.00% (all correct), 98.33% (all correct except one) and 98.66% (all correct except two). Similarly, test dataset accuracy percentages are 96.00% (all correct), 97.00% (all correct except one) and 98.00% (all correct except two).

Table 1: Character regions extraction results for Fold 1

Data	Total Images	X_1	X_2	X_3
Trained	300	291	295	296
Test	200	192	194	196

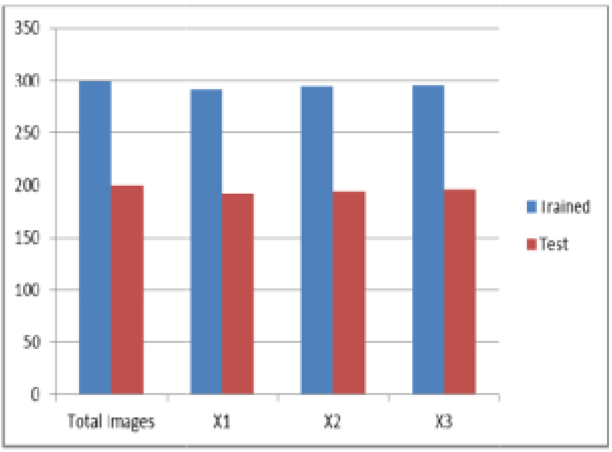

Figure 4: Graph for Character regions extraction (Fold 1)

Where X1: all character regions extracted correctly, X2: character regions extracted correctly except one region, X3: character regions extracted correctly except two regions

For character regions extraction, it is concluded that the success rate for trained images and test images is 97.0% and 96.0% respectively.

The character recognition results are summarized in Table 2 and Figure 5. The recognition accuracy percentages for train datasets are 94.66% (all correct), 97% (all correct except one) and 97.66% (all correct except two). Similarly, test dataset accuracy percentages are 95% (all correct), 95.50% (all correct except one) and 96.50% (all correct except two).

Table 2: Character recognition results for Fold 1

Data	Total Images	Y_1	Y_2	Y_3
Trained	300	287	291	293
Test	200	190	191	193

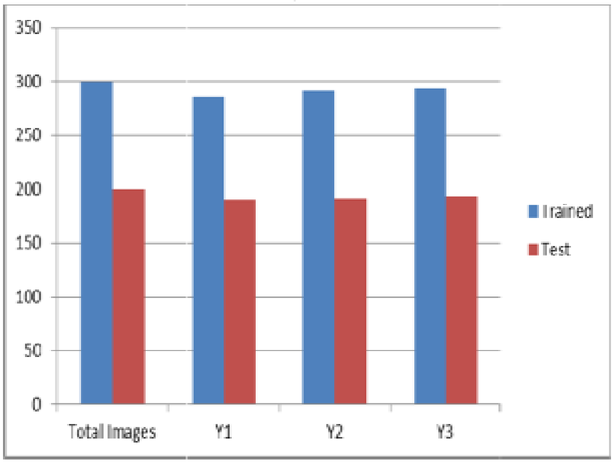

Figure 5: Graph for Character recognition (Fold 1)

Where Y1: all character regions recognized correctly, Y2: character regions recognized correctly except one region, Y3: character regions recognized correctly except two regions.

For character recognition, it is concluded that the success rate for trained images and test images is 95.66% and 95.0% respectively.

B. Results for Fold 2 (Trained Images =250, Test Images=250)

In fold 1, 250 images are taken in training set and another group of 250 images are taken in test set randomly. The system is trained for 250 vehicle images and tested on another 250 vehicle images. The character region extraction results are summarized in Table 3 and Figure 6. The character extraction regions accuracy for train datasets are 97.20% (all correct), 98.00% (all correct except one) and 98.80% (all correct except two). Similarly, test dataset accuracy percentages are 96.40% (all correct), 97.20% (all correct except one) and 97.60% (all correct except two).

For character regions extraction, it is concluded that the success rate for trained images and test images is 97.2% and 96.4% respectively.

For character recognition, it is concluded that the success rate for trained images and test images is 95.60% and 95.80% respectively. The results demonstrate that the proposed technique for Automated Vehicle Plate Recognition system can prove promising in the near future.

Table 3: Character regions extraction results for Fold 2

Data	Total Images	X_1	X_2	X_3
Trained	250	243	245	247
Test	250	241	243	244

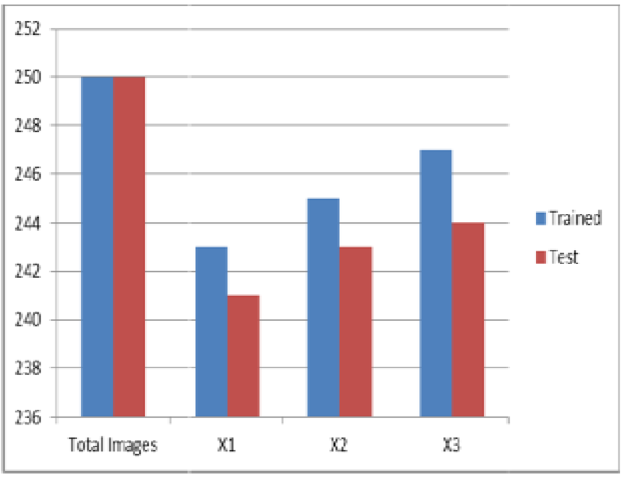

Figure 6: Graph for Character regions extraction (Fold 2)

V. CONCLUSIONS

Vehicle Number Plate Identification is driven by various challenges with an extensive history of research. VNPI systems are constantly being researched. Many endeavors have been performed in the past in implementing such detection systems using a variety of methods. Most of the investigations conducted using vehicle images are based on image processing techniques as far as automation is concerned in the field. Despite the extensive literature and research available on VNPI, the field has not progressed beyond basic knowledge. Therefore, an efficient and accurate license plate recognition model was the need of the hour and thus, got the motivation of the present system to reach a high level of detection and identification rate.

From the current literature in this field of research, it appears that VNPI must overcome difficulties in extracting and more accurately recognizing regions of text to be implemented in real-world situations under a variety of conditions. Since, all the countries have a different system of vehicle number plates, therefore, this domain requires a robust model working for different languages. Moreover, in real time scenario, noisy images are acquired, for instance, in the presence of dust or poor lighting conditions. Consequently, there is need to develop a better system in terms of correctness and consistency for VNPI that can work according to multiple naming conventions in real time scenarios.

Research effort has been intended to come up with a new scientifically validated model for vehicle number plate detection and recognition. In this thesis, a multi-environment VNPI model has been proposed that not only detect the number plates but also high efficiency classification of numbers has been performed. First of all, a database of 500 vehicle images has been randomly created. Thereafter pre-processing has been performed for resizing and improving the image quality. Afterwards, based on the image shape features, regions are being segmented and both inter and overlapping characteristics of the regions are considered as a similarity and dissimilarity measure for region extraction. Thereafter, correlation of the neighboring pixels is computed to find out the similarity between the regions.

The proposed VNPI model very well extracted the segments around the characters with extraction rate of 96.69% and recognition rate of 95.34%. Experimental results show that the proposed technique is simple and robust. The results are comparable with the results of the state-of-art methods available in the literature.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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