

ISSN: 0067-2904

# An Improved Method to Recognize the Iraqi License Plates Using Local Projections 

Nada Najeel Kamal ${ }^{1 *}$, Loay Edwar George ${ }^{2}$<br>${ }^{1}$ Department of Computer Science, University of Technology, Baghdad, Iraq.<br>${ }^{2}$ Department of Computer Science, University of Baghdad, Baghdad, Iraq.


#### Abstract

The License Plate (LP), is a rectangular metal plate that contains numbers and letters. This plate is fixed onto the vehicle's body. It is used as a mean to identify the vehicle. The License Plate Recognition (LPR) system is a mean where a vehicle can be identified automatically using a computer system. The LPR has many applications, such as security applications for car tracking, or enforcing control on vehicles entering restricted areas (such as airports or governmental buildings). This paper is concerned with introducing a new method to recognize the Iraqi LPs using local vertical and horizontal projections, then testing its performance. The attained success rate reached $99.16 \%$, with average recognition time around 0.012 second for recognizing a single alphanumeric symbol .


Keywords:License plate,Recognition, Local Projection, Alphanumeric Recognition.


الخلاصة

$$
\begin{align*}
& \text { ان لوحة نسجيل السيارة (LP) عبارة عن صفيحة معدنية تحوي أرقام وحروف، ويتم تثبت اللوحة على } \\
& \text { جسم العربة. وهي تستخدم كوسيلة للتعرف على العربة. ان نظام تمييز لوحات التنجيل LPR هو الوسيلة التي } \\
& \text { يمكن من خلالها التعرف على العربة بشكل آلي بأستخدام نظام الحاسوب. ان نظام تمييز اللوحات (LPR) لـ } \\
& \text { تطبيقات عدة، مثل التطبيقات الأمنية المتعلقة بتتبع السيارات، أو فرض السبطرة على دخول العربات لمنطقة } \\
& \text { محددة (كالمطارات أو المباني الحكومية). تغنى هذه المقالة البحثية باقتراح طريقة جديدة لتمييز لوحات تسجيل } \\
& \text { السيارات العراقية بأستخدام الأسقاطات المحلية العمودية والأفقية، ومن ثم اختبار اداؤها. ان نسبة التمبيز التي } \\
& \text { تم النوصل اليها وصلت إلى 99.16\% وبمعدل وقت للتميز حالي } 0.012 \text { ثانية لتمييز اي شكل لحرف أو } \tag{رقم.}
\end{align*}
$$

## 1. Introduction

Since the number of vehicles is increasing largely every year, then the process of controlling and tracking those vehicle forms a significant human challenge. The automatic recognition of those

[^0]vehicles can help in solving this problem, and save much effort and time. The License Plate Recognition (LPR) system is a form of automatic vehicle identification.

The applications of the LPR are varied, they may include: stolen cars tracking, parking control, enforcing the entry for authorized people to certain areas, and speed control.

The first LPR system was appeared in United Kingdom in 1976. Since that moment; many countries applied automatic LPR systems ${ }^{i}$, officially, but Iraq was not among them. This stimulated researchers attention to develop new methods to recognize the Iraqi License plates (LP) using Local vertical and horizontal projections.

## 2. Related Works

Many researches tackled the problem of recognizing the extracted alphanumerics objects from LPs for different countries. These researches explored different methods, algorithms and techniques. Scope of the recently used methods and techniques are reviewed below. The facts that are mentioned about the surveyed literatures depend on what is documented in them.
Template matching is a popular method that is used in many researches. Devapriy and et al. [1] used Template matching to find the similarities between a predefined template and input image. The cross correlation template matching technique is used to recognize the LP characters. Two common matching functions are used to find an exact or a close match. A collection consists of 500 car images of Indian LPs were tested in their research, they referred that the best attained success rate was $(98 \%)$. The template matching was used by Sharma and et al. [2] to compute the correlation between the template and a segmented block of character. The maximum size of the used images reached to $603 \times 399$ pixels. There was no clear Figures in their research paper clarify the number of images used in testing phase and about the best attained recognition rate. In this literature, also, there is no documentation about the core features used to recognize the LP characters, and the distance measure is not presented too.

Also, template matching was applied by Basalamah [3] for comparing the segmented Saudi License plates with the reference templates using simple certain comparison equation, in which all of segmented images are compared to a reference template. The character images are normalized to the size of $50 \times 50$ pixels. The total number of the used images was 140 LP image. The success rate reached to $81 \%$.

Cheng and Bai [4] used a cascade consists of two steps template matching which are based on the Connected Domain Feature (CDF) and the Standard Deviation Feature (SDF), respectively. The images are normalized to the size of $32 \times 16$ pixels. A set of 322 Chinese character images were used. The number of correctly passed images was 309 (which corresponds to success rate $95.99 \%$ ).

Neural networks methodology is commonly used in many researches to recognize the LP characters and numerals. Laxmi and Rohil [5] have used the features of the segmented LP characters which are extracted using Haar Wavelet, and then recognize them using back propagation neural network. Different numbers of car images were used to test the system. The best achieved success rate was around $88 \%$ when 30 image are exploited for the training issues, while the elapsed time was 42 seconds.

To recognize the LP of Nigerian vehicles, the neural network was used by Amusan and et al [6]. The weights of the neural network were adjusted by training it using back propagation algorithm. Different categories of plates were used to test this system. The highest success rate that is registered in this work reached $96.25 \%$ when 320 character images were tested, and the processing time was 3.62 second.

The recognition of LPs was experimented by Ganapathy and Lui [7]; was done through the implementation of feed-forward backpropagation artificial neural network. The images of segmented LP characters were normalized to fix size of $25 \times 15$ pixels. A set of 589 Malaysian car images were used to test the system, $95 \%$ of these images have pass the recognition test.
Perwej and et al. [8] have applied the Learning Vector Quantization artificial neural network to implement the recognition of LPs. The images were normalized to the size of $150 \times 100$. The total number of used car image was 350 images. The success rate reached $94.91 \%$.

To identify the vehicles in Kurdistan Region of Iraq, an approach was used by Ali and et al. [9]; it was based on using the concept of Gabor feature vector and different classifiers (i.e., support vector machines, K-nearest neighbors and Radial basis function) in order to classify the LP features. A set
consists of 1000 car images used as test material. The size of each image was normalized to the size $309 \times 240$ pixels. The attained recognition success was $96.72 \%$.
Also, the K-Nearest neighbor method was used by Azad and et al. [10] to recognize the Iranian LPs. In this work, a set of 800 character images were extracted from the LPs. The number of correctly recognized images was (792), which corresponds to success rate (99.12\%).

The optical character recognition that uses the correlation method to match each individual LP alphanumeric was applied by Sutar and Shah [11]. The images were normalized to the size of $1536 \times 2048$ or $640 \times 480$. The total tested LP image was 90 . Eighty four images were correctly passed the test; which corresponds to recognition rate ( $93 \%$ ). The whole processing time was 45 seconds.
Sarker and Song [12] have used a set of features based on Local Line Binary Pattern (LLBP). This method includes obtaining a binary code with respect to the horizontal and vertical direction individually as the first step. While the second step is computing the magnitude, which typifies the variation in image intensity such as edges and corners. Hamming Distance was used as a similarity measure. A set consist of 1000 of Korean LP images were tested. The recognition rate reached to 97.74\%.

Ashtari and et al. [13] have studied the use of a hybrid classifier that comprises a decision tree and support vector machine to classify the features that are extracted from the LP images of Iranian LPs. As an example for the extracted features: the number of holes in the character, which is called Euler number, also the periodic vertical and horizontal searches to find changes in edge, in addition to dividing a character into a predefined number of tiles, such as $6 \times 4$ or $4 \times 6$ or $5 \times 5$ and then using the ratio of object pixels to background pixels of each tile is a proper feature for recognition. The attained recognition rate was ( $94.4 \%$ ).

From the point view of networks, the connectivity of image pixels can be considered as complex network, based on the previous statement Ren and Ma [14] had conducted their research. In this paper the skeleton of characters is extracted from Chinese LPs using thinning algorithm; then it is mapped to a weighted complex network. The feature vector of the network was used as a template. The images are normalized to the size of $40 \times 20$ pixels. The attained recognition rate was $98.19 \%$ for 700 character samples. The average processing time was 33.63 milliseconds per character.
A comparison between the letters and numbers extracted from Iraqi LP (used in Kurdistan Provinces) with the corresponding templates registered in a pre-established database was done by Aziz [15]. No details were mentioned about the tests steps. A set consists of 57 car images was used as testing material, 54 images were recognized successfully.

Two approaches have been used by Kamal and George [16, 17] to recognize the Iraqi license plates. The first method is the moment based method, the second method is the local density distribution method. Different types of tests were experimented in this paper. A set consists of 1784 LP characters images were used as testing samples. The best success rates for the used methods was $92.49 \%$ and $98.99 \%$, respectively.

## 3. System Layout

Generally, any LPR system using video frames or still images consists of basic phases, it may include: image acquisition, preprocessing, LP extraction, LP alphanumeric objects segmentation, and LP alphanumeric recognition. The general layout for the proposed system is presented in Figure- 1.


Figure 1- The diagram of the introduced vertical and horizontal projections based system for automatic LPR.

### 3.1 Preprocessing

The applied preprocessing stage involves three basic steps to prepare the image for recognition stage. These steps include: converting the image to gray one, convert this gray image to a binary one, and then normalizing the image dimensions. These steps are explained in details below.

## A. Getting the Gray Image

Since the alphanumeric images come in 24 bit per pixel as a depth for each pixel in the image, the image bands of red, green and blue are extracted for each of the tested images. Then, the gray image is obtained using equation 1 .
$\operatorname{Gray}(i, j)=(\operatorname{Red}(i, j)+\operatorname{Green}(i, j)+$ Blue $(i, j)) / 3$
Where the pixel at the location $(i, j)$ in the Gray image is obtained as the average of red, green, and blue bands.

## B. Getting the Binary Image

The goal of this stage is the conversion of alphanumeric gray image into a binary form. The region of interest of the alphanumeric shape will be turned to white, while the background will be mapped to a black color.

A threshold of 128 was used to convert the alphanumeric image to the required binary image. 128 represents the mid value of the range between 0 and 255 . To get the binary image, the pixels of the gray image are scanned to specify if the pixel value met the condition of being less than the threshold value, then, it will be turned to 1 , otherwise it will be set to 0 .

## C. Equalization of Image Dimensions

Image dimensions equalization implies making its height and width equal. Making image dimensions equal will lead to equal areas and, consequently equal number of blocks, for gaining local set of features each subset represents certain spatial behavior of the alphanumeric object. To get images with equalized dimensions, zero padding method was applied along the both sides of the shortest dimension of the binary image. The applied preprocessing steps are clarified in Figure- 2.

[^1]The number of all blocks equals to the squared number of blocks along one of the two dimensions. That means if the image is partitioned into four blocks along certain dimension, this will lead to sixteen ( $4^{2}$ ) blocks over all image segment.

For each block (or tile) of the image, the vertical and the horizontal projections are calculated. The value of these projections will be stored in two arrays, each of these arrays is a one dimensional array; i.e., $\mathrm{V}(\mathrm{Y})$ for the vertical projection and $\mathrm{H}(\mathrm{X})$ for the horizontal projection. These two arrays will represent the features of each segment.

The lines of the binary block will be scanned for each direction individually. The cell of the projection array of a direction will be set to 1 whenever $a$ white pixel is encountered in the scanned line of the specified direction for the local part of the binary image of the alphanumeric. See Figure- 3.


Figure 3- An illustration of feature extraction steps.

### 3.3 Template Creation and Matching Equations

The number of features ( $\mathrm{n}_{\text {feat }}$ ) that is extracted from a single image segment equals to what is shown in the following equation:
$n_{\text {feat }}=2 * N$,
Where, $N$ refers to the number of tiles along each direction for each image segment.
The mean and standard deviation vectors for the extracted feature vectors from the training set of samples were determined and used as templates for representing each class of alphanumeric segment. Single mean and standard deviation vector is assigned for each template.

For each image class, $70 \%$ of the total images have been used to create the templates. Note, that there are 8 classes, each of which contains six or less than this number as image samples, so for these
cases all samples were included to determine the corresponding templates. The class numbers for these small classes are ( $10,12,16,17,23,25,26$, and class 27), as shown in Table 1.
For matching task, four different equations have been used as similarity distance measures to determine the membership of the tested input alphanumeric image for certain class. The used distance measures are described in the equations:
$D_{1}(i, j)=\sum_{\substack{k=1 \\ N_{f \text { eat }}}}^{N_{f \text { eat }}}\left(\frac{f_{i}(k)-\mu_{j}(k)}{\sigma_{j}(k)}\right)^{2}$

Where, $D$ is the distance between the $i^{\text {th }}$ input feature vector, $f_{i}()$, and the $\mathrm{j}^{\text {th }}$ template vector; k represents the feature index number. The range of values of $i$ and $j$ depends on the total number of classes (i.e., [0-27]). $N_{\text {feat }}$ is the number extracted features from each segment sample. $\mu$ denotes for the mean, while $\sigma$ refers to the standard deviation value.

## 4. The Database

The sample images used to test the proposed system have been extracted by the researchers using different photos for various versions of Iraqi license plates, which have different styles. There are many differences between the LP belong to different versions. The total number of samples was 1785 image sample. They are classified manually by the researchers into 28 classes. Each class holds different number of image samples. The alphanumeric classes with their corresponding numbers of samples are listed in Table- 1.

All these images are stored as Bitmap (BMP) files, with the color depth 24 bits per pixel. The size of these images ranges from $11 \times 13$ to $284 \times 245$ pixels. All images come in a form such that the foreground color of alphanumeric body is black, while the background color is set to white.

Table 1- The database of the 28 used classes with the number of image samples of each class.

| A Sample from the Class | $\begin{gathered} \text { Class } \\ \text { Index } \\ \text { Number } \end{gathered}$ | Number of Samples per Class | A Sample from the Class | $\begin{gathered} \hline \text { Class } \\ \text { Index } \\ \text { Number } \\ \hline \end{gathered}$ | Number of Samples per Class |
| :---: | :---: | :---: | :---: | :---: | :---: |
| - | 0 | 88 | 1 | 14 | 67 |
| 1 | 1 | 126 | $1$ | 15 | 12 |
| 9 | 2 | 198 | 5 | 16 | 4 |
| $\underline{N}$ | 3 | 97 | $14$ | 17 | 2 |
| 2 | 4 | 114 | (1) | 18 | 14 |
| 0 | 5 | 99 | $v^{n-9}$ | 19 | 13 |
| 7 | 6 | 175 | $4$ | 20 | 68 |
| $V$ | 7 | 130 | 19 | 21 | 12 |
| 1 | 8 | 75 | gil | 22 | 160 |
| $9$ | 9 | 109 | $s$ | 23 | 3 |
| 8 | 10 | 4 |  | 24 | 13 |
| 1-3 | 11 | 174 | 4-3) | 25 | 4 |
| $\xrightarrow{1}$ | 12 | 6 | $L$ | 26 | 3 |
| guas | 13 | 13 | $1$ | 27 | 2 |
| Total Number of Samples $=1785$ |  |  |  |  |  |

## 5. Tests Results

Three strategies were used to test the proposed method. For all of these three tests, the four distance measures mentioned in the above section were tested individually. The percentage of the true positive samples is calculated, and the required time for single alphanumeric image is documented. In these strategies different number of tiles per image is tested (i.e., $2 \times 2$ to $20 \times 20$ tiles). The considered rate of overlapping was taken from 0 to 1 .
For strategy (A) the $70 \%$ of the samples (which already used as training samples) for each class were tested. Table- 2 shows the test results of this strategy. In this table, the best attained results are marked in red.

In Strategy (B) the remaining $30 \%$ of samples of each class were tested. This strategy is considered as hard test of the system. Notice here that the 8 classes that have six or less samples are included in this test also, as shown in Table 3. The best attained results are highlighted in red.
For strategy (C), all samples (i.e., 1785) samples are included in this test. This test is considered as a comprehensive test. Table- 4 shows the best attained results that are highlighted with red.

Table 2- Test result for strategy A, where all trained samples were used.

| Total <br> Number <br> of tested <br> Samples | True <br> Positive | Percentage | Time <br> (S) | Number <br> of Blocks | Rate of <br> Overlapping | Distance <br> Measure <br> Equation |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1318 | 1310 | 99.393 | 0.02 | $14 \times 14$ | 0.8 | 3 |
| 1318 | 1293 | 98.103 | 0.026 | $18 \times 18$ | 1 | 4 |
| 1318 | 1261 | 95.675 | 0.019 | $16 \times 16$ | 0.9 | 5 |
| 1318 | 1261 | 95.675 | 0.019 | $16 \times 16$ | 0.9 | 6 |

Table 3- Test results for strategy B, only the non-training samples were used.

| Total <br> Number <br> of tested <br> Samples | True <br> Positive | percentage | Time <br> (S) | Number <br> of <br> Blocks | Rate of <br> Overlapping |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 495 | 493 | 99.59596 | 0.005 | $7 \times 7$ | 0.1 |
| Measure |  |  |  |  |  |
| Equation |  |  |  |  |  |$|$

Table 4- Test result for strategy C, where all of the samples were used.

| Total <br> Number <br> of tested <br> Samples | True <br> Positive | percentage | Time <br> (S) | Number <br> of <br> Blocks | Rate of <br> Overlapping | Distance <br> Measure <br> Equation |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 1785 | 1770 | 99.160 | 0.012 | $12 \times 12$ | 0.8 | 3 |
| 1785 | 1753 | 98.207 | 0.007 | $10 \times 10$ | 0.1 | 4 |
| 1785 | 1712 | 95.910 | 0.019 | $16 \times 16$ | 0.9 | 5 |
| 1785 | 1743 | 97.647 | 0.019 | $16 \times 16$ | 1 | 6 |

Depending on strategy (C), the attained recognition rate is $\mathbf{9 9 . 1 5 9 \%}$ (i.e., 1770 image sample passed successfully the tests among the total 1785 samples). The best attained result is higher than all of the reviewed literatures. The details of test (C) is presented in Table 5-a and Table 5-b.
In Table 5-a the test results for strategy C is presented, where all of 1785 samples were tested. For this Table the number of blocks was taken from $2 \times 2$ to $10 \times 10$. For Table 5 -b test results for strategy C is presented. In this Table all of the 1785 samples were tested too, while the number of blocks ranges from 11x11 to $20 \times 20$.

For both of the two Tables, Table 5-a and Table 5-b, the rate of overlapping ranges from 0 to 1 . The documented time is in seconds, which is given as an average time for recognizing a single alphanumeric image.

One can notice that the best recognition rate is obtained when the number of features equals $12 \times 12 \times 2$ with rate of overlapping ration reaches to $80 \%$. The average time for the recognition of single alphanumeric is 0.012 second. This result was gained when the distance measure $\left(D_{1}\right)$ was used for testing the similarity between templates features and the corresponding features of the tested input alphanumeric samples. Table 6 shows the details of this obtained result.

## 6. Conclusions

This paper presents a new method to recognize the letters and numbers of the Iraqi LP. The used method extracts the features from the binary image of the alphanumeric by partitioning it into tiles, then for each tile, the vertical and horizontal projections are determined. A set consists of 1785 images
were used test the performance of the proposed method using four different similarity measures. Three test strategies were applied to test the proposed method. The results show that the local vertical and horizontal projections are suitable for representing alphanumeric objects of the Iraqi license plate, it leads to success recognition rate reaches to $99.15966 \%$. By comparing this result with many recent published researches, one can conclude that the proposed method shows the best performance. In future scope this method can be developed and used for scanned images recognition, or handwritten letters and numerals. Also, instead of still images, capturing the plate images from a video to have a real time system may be adopted too.

Table 5-a: Details of test strategy C, with number of blocks ranges from $2 \times 2$ to $10 \times 10$.

| R |  | Number of Blocks |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | $2 \times 2$ | 3x3 | 4×4 | 5x5 | $6 \times 6$ | 787 | 8x8 | 9x9 | 10x10 |
| 0 | TP | 1666 | 1476 | 1727 | 1690 | 1732 | 1761 | 1757 | 1762 | 1743 |
|  | \% | 93.33334 | 82.68908 | 96.7507 | 94.67787 | 97.03082 | 98.65546 | 98.43137 | 98.71149 | 97.64706 |
|  | Tlime(S) | 0.001 | 0.002 | 0.002 | 0.003 | 0.003 | 0.004 | 0.005 | 0.006 | 0.007 |
| 0.1 | TP | 1519 | 1594 | 1720 | 1710 | 1744 | 1762 | 1746 | 1758 | 1755 |
|  | \% | 85.09804 | 89.29972 | 96.35854 | 95.79832 | 97.70308 | 98.71149 | 97.81512 | 98.4874 | 98.31933 |
|  | Tlime(S) | 0.001 | 0.002 | 0.002 | 0.003 | 0.004 | 0.004 | 0.005 | 0.006 | 0.007 |
| 0.2 | TP | 1370 | 1638 | 1710 | 1741 | 1741 | 1754 | 1753 | 1760 | 1762 |
|  | \% | 76.7507 | 91.76471 | 95.79832 | 97.53501 | 97.53501 | 98.26331 | 98.20728 | 98.59944 | 98.71149 |
|  | Tlime(S) | 0.002 | 0.002 | 0.002 | 0.003 | 0.004 | 0.004 | 0.005 | 0.006 | 0.008 |
| 0.3 | TP | 1154 | 1690 | 1682 | 1736 | 1737 | 1731 | 1749 | 1748 | 1761 |
|  | \% | 64.64986 | 94.67787 | 94.22969 | 97.25491 | 97.31092 | 96.97479 | 97.98319 | 97.92717 | 98.65546 |
|  | Tlime(S) | 0.002 | 0.002 | 0.003 | 0.003 | 0.004 | 0.005 | 0.006 | 0.007 | 0.008 |
| 0.4 | TP | 1059 | 1704 | 1656 | 1721 | 1744 | 1722 | 1763 | 1751 | 1757 |
|  | \% | 59.32773 | 95.46218 | 92.77311 | 96.41457 | 97.70308 | 96.47059 | 98.76751 | 98.09524 | 98.43137 |
|  | Tlime(S) | 0.002 | 0.002 | 0.003 | 0.004 | 0.004 | 0.005 | 0.006 | 0.007 | 0.008 |
| 0.5 | TP | 821 | 1656 | 1675 | 1710 | 1729 | 1722 | 1750 | 1757 | 1762 |
|  | \% | 45.9944 | 92.77311 | 93.83753 | 95.79832 | 96.86275 | 96.47059 | 98.03922 | 98.43137 | 98.71149 |
|  | Tlime(S) | 0.002 | 0.003 | 0.003 | 0.004 | 0.004 | 0.005 | 0.006 | 0.007 | 0.008 |
| 0.6 | TP | 715 | 1558 | 1705 | 1688 | 1745 | 1737 | 1758 | 1746 | 1757 |
|  | \% | 40.05602 | 87.28291 | 95.5182 | 94.56583 | 97.7591 | 97.31092 | 98.4874 | 97.81512 | 98.43137 |
|  | lime(S) | 0.002 | 0.003 | 0.003 | 0.004 | 0.005 | 0.005 | 0.007 | 0.007 | 0.009 |
| 0.7 | TP | 685 | 1404 | 1696 | 1649 | 1743 | 1730 | 1760 | 1738 | 1755 |
|  | \% | 38.37535 | 78.65546 | 95.01401 | 92.38095 | 97.64706 | 96.91877 | 98.59944 | 97.36694 | 98.31933 |
|  | lime(S) | 0.002 | 0.003 | 0.004 | 0.004 | 0.005 | 0.006 | 0.007 | 0.008 | 0.009 |
| 0.8 | TP | 636 | 1318 | 1696 | 1648 | 1734 | 1728 | 1756 | 1753 | 1762 |
|  | \% | 35.63025 | 73.83753 | 95.01401 | 92.32493 | 97.14286 | 96.80672 | 98.37535 | 98.20728 | 98.71149 |
|  | Time(S) | 0.003 | 0.003 | 0.004 | 0.004 | 0.005 | 0.006 | 0.007 | 0.008 | 0.009 |
| 0.9 | TP | 663 | 1157 | 1698 | 1645 | 1719 | 1731 | 1745 | 1754 | 1755 |
|  | \% | 37.14286 | 64.81792 | 95.12605 | 92.15686 | 96.30252 | 96.97479 | 97.7591 | 98.26331 | 98.31933 |
|  | Time(S) | 0.003 | 0.004 | 0.004 | 0.005 | 0.006 | 0.006 | 0.007 | 0.008 | 0.01 |
| 1 | TP | 2 | 1077 | 1671 | 1663 | 1716 | 1738 | 1745 | 1757 | 1759 |
|  | \% | 0.1120448 | 60.33614 | 93.61345 | 93.16527 | 96.13445 | 97.36694 | 97.7591 | 98.43137 | 98.54342 |
|  | Tlime(S) | 0.003 | 0.004 | 0.004 | 0.005 | 0.006 | 0.007 | 0.008 | 0.009 | 0.01 |

Table 5-b: Details of test strategy C, with number of blocks ranges from 11x11 to 20x20.

| R |  | Nunmer of Blocks |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 11×11 | 12×12 | 13×13 | 14×14 | 15×15 | 16x16 | 17x17 | 18×18 | 19×19 | 20x20 |
| 0 | TP | 1754 | 1750 | 1735 | 1732 | 1735 | 1738 | 1731 | 1727 | 1708 | 1724 |
|  | \% | 98.26331 | 98.03922 | 97.19888 | 97.03082 | 97.19888 | 97.36694 | 96.97479 | 96.7507 | 95.68627 | 96.58263 |
|  | Time(S) | 0.008 | 0.01 | 0.011 | 0.013 | 0.014 | 0.016 | 0.018 | 0.02 | 0.022 | 0.024 |
| 0.1 | TP | 1752 | 1746 | 1738 | 1725 | 1733 | 1743 | 1740 | 1732 | 1730 | 1711 |
|  | \% | 98.15126 | 97.81512 | 97.36694 | 96.63866 | 97.08684 | 97.64706 | 97.47899 | 97.03082 | 96.91877 | 95.85434 |
|  | Time (S) | 0.008 | 0.01 | 0.011 | 0.013 | 0.014 | 0.016 | 0.018 | 0.02 | 0.022 | 0.025 |
| 0.2 | TP | 1759 | 1753 | 1753 | 1747 | 1742 | 1736 | 1737 | 1738 | 1735 | 1735 |
|  | \% | 98.54342 | 98.20728 | 98.20728 | 97.87115 | 97.59103 | 97.25491 | 97.31092 | 97.36694 | 97.19888 | 97.19888 |
|  | Time(S) | 0.009 | 0.01 | 0.012 | 0.013 | 0.015 | 0.017 | 0.018 | 0.021 | 0.023 | 0.025 |
| 0.3 | TP | 1756 | 1758 | 1755 | 1752 | 1743 | 1737 | 1734 | 1736 | 1740 | 1734 |
|  | \% | 98.37535 | 98.4874 | 98.31933 | 98.15126 | 97.64706 | 97.31092 | 97.14286 | 97.25491 | 97.47899 | 97.14286 |
|  | Time(S) | 0.009 | 0.01 | 0.012 | 0.013 | 0.015 | 0.017 | 0.019 | 0.021 | 0.023 | 0.025 |
| 0.4 | TP | 1746 | 1762 | 1760 | 1754 | 1750 | 1743 | 1748 | 1736 | 1738 | 1742 |
|  | \% | 97.81512 | 98.71149 | 98.59944 | 98.26331 | 98.03922 | 97.64706 | 97.92717 | 97.25491 | 97.36694 | 97.59103 |
|  | Time(S) | 0.009 | 0.011 | 0.012 | 0.014 | 0.016 | 0.017 | 0.019 | 0.021 | 0.023 | 0.025 |
| 0.5 | TP | 1746 | 1764 | 1758 | 1758 | 1753 | 1746 | 1753 | 1740 | 1739 | 1731 |
|  | \% | 97.81512 | 98.82353 | 98.4874 | 98.4874 | 98.20728 | 97.81512 | 98.20728 | 97.47899 | 97.42297 | 96.97479 |
|  | Time(S) | 0.01 | 0.011 | 0.012 | 0.014 | 0.016 | 0.018 | 0.019 | 0.021 | 0.023 | 0.026 |
| 0.6 | TP | 1751 | 1763 | 1765 | 1760 | 1758 | 1757 | 1759 | 1752 | 1755 | 1744 |
|  | \% | 98.09524 | 98.76751 | 98.87955 | 98.59944 | 98.4874 | 98.43137 | 98.54342 | 98.15126 | 98.31933 | 97.70308 |
|  | Time(S) | 0.01 | 0.011 | 0.013 | 0.014 | 0.016 | 0.018 | 0.02 | 0.022 | 0.024 | 0.026 |
| 0.7 | TP | 1760 | 1763 | 1768 | 1757 | 1765 | 1766 | 1755 | 1764 | 1752 | 1746 |
|  | \% | 98.59944 | 98.76751 | 99.04762 | 98.43137 | 98.87955 | 98.93558 | 98.31933 | 98.82353 | 98.15126 | 97.81512 |
|  | Time(S) | 0.01 | 0.011 | 0.013 | 0.015 | 0.016 | 0.018 | 0.02 | 0.022 | 0.024 | 0.027 |
| 0.8 | TP | 1761 | 1770 | 1764 | 1769 | 1762 | 1766 | 1762 | 1766 | 1757 | 1763 |
|  | \% | 98.65546 | 99.15966 | 98.82353 | 99.10364 | 98.71149 | 98.93558 | 98.71149 | 98.93558 | 98.43137 | 98.76751 |
|  | Tlime(S) | 0.01 | 0.012 | 0.013 | 0.015 | 0.017 | 0.018 | 0.02 | 0.022 | 0.025 | 0.027 |
| 0.9 | TP | 1761 | 1766 | 1769 | 1769 | 1766 | 1768 | 1761 | 1757 | 1752 | 1761 |
|  | \% | 98.65546 | 98.93558 | 99.10364 | 99.10364 | 98.93558 | 99.04762 | 98.65546 | 98.43137 | 98.15126 | 98.65546 |
|  | Time(S) | 0.011 | 0.012 | 0.014 | 0.015 | 0.017 | 0.019 | 0.021 | 0.023 | 0.025 | 0.027 |
| 1 | TP | 1764 | 1763 | 1766 | 1765 | 1769 | 1770 | 1763 | 1767 | 1760 | 1767 |
|  | \% | 98.82353 | 98.76751 | 98.93558 | 98.87955 | 99.10364 | 99.15966 | 98.76751 | 98.9916 | 98.59944 | 98.9916 |
|  | Time(S) | 0.011 | 0.013 | 0.014 | 0.016 | 0.017 | 0.019 | 0.021 | 0.023 | 0.025 | 0.027 |

Table 6- Details of the attained results for the all samples belong to 28 classes. The number of tiles is $12 \times 12$ with overlapping ratio (0.08).

| Class <br> No. | No. of <br> Samples <br> Per Class | True <br> Positive | \% | Class <br> No. | No. of <br> Samples <br> Per Class | True <br> Positive | \% |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 88 | 87 | 98.864 | 15 | 12 | 12 | 100 |
| 1 | 126 | 125 | 99.206 | 16 | 4 | 4 | 100 |
| 2 | 198 | 196 | 98.990 | 17 | 2 | 2 | 100 |
| 3 | 97 | 97 | 100 | 18 | 14 | 14 | 100 |
| 4 | 114 | 113 | 99.123 | 19 | 13 | 11 | 84.615 |
| 5 | 99 | 97 | 97.980 | 20 | 68 | 66 | 97.059 |
| 6 | 175 | 175 | 100 | 21 | 12 | 12 | 100 |
| 7 | 130 | 129 | 99.231 | 22 | 160 | 159 | 99.375 |
| 8 | 75 | 73 | 97.333 | 23 | 3 | 3 | 100 |
| 9 | 109 | 109 | 100 | 24 | 13 | 13 | 100 |
| 10 | 4 | 4 | 100 | 25 | 4 | 4 | 100 |
| 11 | 174 | 174 | 100 | 26 | 3 | 3 | 100 |
| 12 | 6 | 6 | 100 | 27 | 2 | 2 | 100 |
| 13 | 13 | 13 | 100 | Total: 28 | 1785 | 1770 | $99.15966 \%$ |
| 14 | 67 | 67 | 100 | $C l a s s e s$ |  |  |  |

## References

1. Devapriy, W., Nelson Kennedy Babu, C., and Srihari, T. 2015. Indian License Plate Recognition using morphological operation and template matching. International Journal of Computer, Electrical, Automation, Control and Information Engineering. 9(4), pp. 1003-1009.
2. Sharma, V., Mathpal, P. C., and Kaushik, A. 2014. Automatic license plate recognition using optical character recognition and template matching on yellow color license plate. International Journal of Innovative Research in Science, Engineering and Technology (2319-8753). 3(5), pp. 12984-12990.
3. Basalamah, S. 2013. Saudi License Plate Recognition. International Journal of Computer and Electrical Engineering. 5(1), pp. 1-4.
4. Cheng,R. and Bai, Y. 2014. Novel Approach for License Plate Slant Correction, Character Segmentation and Chinese Character Recognition. International Journal of Signal Processing, Image Processing and Pattern Recognition. 7(1), pp. 353-364.
5. Laxmi, V. and Rohil, H. 2014. License Plate Recognition System using Back Propagation Neural Network. International Journal of Computer Applications (0975 - 8887). 99(8), pp. 29-37.
6. Amusan D.G., Arulogun O.T, and Falohun A. S.2015. Nigerian Vehicle License Plate Recognition System using Artificial Neural Network. International Journal of Advanced Research in Computer and Communication Engineering. 4(11), pp. 1-5.
7. Ganapathy, V. and Lui, W. D. A Malaysian Vehicle License Plate Localization and Recognition System. Systemics, Cybernetics and Informatics (1690-4524). 6(1), pp. 13-20.
8. Perwej, y., Akhtar, N. and Parwej, F. The Kingdom of Saudi Arabia Vehicle License Plate Recognition using Learning Vector Quantization Artificial Neural Network. 2014. International Journal of Computer Applications (0975 - 8887). 98(11), pp. 32-38.
9. Ali, A. M., Shareef, S. M. and Rashid, T. A. 2015. Automatic License Plate Recognition in Kurdistan Region of Iraq (KRI), Journal of Zankoi Sulaimani, Part-A- (Pure and Applied Sciences),(17), pp: 235-244.
10. Azad, R., Azad, B. and Brojeeni, H. 2013. Real-Time and Efficient Method for Accuracy Enhancement of Edge Based License Plate Recognition System. First International Conference on computer, Information Technology and Digital Media (CITADIM Proceeding-Scientific).
11. Sutar, G. T. and Shah, A. V. 2014. Number Plate Recognition Using an Improved Segmentation. International Journal of Innovative Research in Science, Engineering and Technology (23198753), 3(5), pp. 12360-12368.
12. Sarker, M. K. and Song, M. K. 2015. Korean Car License Plate Character Recognition using Local Line Binary Pattern. Korea Information and Communications Society General Conference Proceedings (Winter) 2015, Gangwon do , Korea. 20-21 Jan, pp. 112-114.
13. Ashtari, A. H., Nordin, M. J., and Fathy, M. 2014. An Iranian License Plate Recognition System Based on Color Features. IEEE Transactions on Intelligent Transportation Systems., pp. 1-16.
14. Ren. H., and Ma Z. License Plate Recognition Using Complex Feature. Proceeding of the $11^{\text {th }}$ World Congress on Intelligent Contro Control and Automation. Shenyang, China, 29 June -July.
15. Aziz, M. M. 2016. Ishik University Gate Control based on Kurdistan License Plat. International Journal of Enhanced Research in Science, Technology \& Engineering (2319-7463). 5 (1), pp. 3438.
16. 16. Kamal, N. N. and George, L. E. License Plate Numerics and Characters Recognition International Journal of Advanced Research in Computer Science and Software Engineering. 4(4), pp. 824-835.
1. Kamal, N. N. and George, L. E. 2013. A Localization System for Car License Plate. International Journal of Scientific \& Engineering Research (2229-5518). 4(6), pp. 831-838

[^0]:    *Email: nadanajeelkamal@yahoo.com

[^1]:    
    (a) Gray image of number four
    
    (d) Gray image of "بغد" segment of Baghdad word
    
    (b) Binary image of number four with height greater than width
    (e) Binary image of "بغ" segment of Baghdad word with width greater than height
    
    (c) Equalized height and width for the binary image of number four
    
    (f) Equalized height and width for the binary image of "بغ" segment of Baghdad word

    Figure 2-Preprocessing Steps.

    ### 3.2 Feature Extraction using Local Projections

    This stage was used to get the image features, and then the extracted features are used to recognize the alphanumeric image. This step includes partitioning the binary image of the equalized dimension into overlapped blocks. Since the image block is equalized in its dimensions, then the image blocks will set to same size; this means that all the processed blocks will have same number of pixels. These blocks will be overlapped or interlaced to certain ratios. The overlapping leads to better recognition rates, because it is compensate for the local drifts, and deviations related to the shape of the alphanumeric for image samples in the same class.

