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License Plate Recognition using CNN and OCR on SMQT Images Obtained from RANSAC Algorithm

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Abstract
Now a days the count of vehicles increases day by day. Due to different plate layout and fonts recognition is difficult in some situation of the identification of license plaques plays an important role in transport systems. The License plate region is localized by Random Sample Consensus (RANSAC) algorithm. Then the Successive Mean Quantization Transform (SMQT) is applied to the localized region to focus on the details of the region. The SMQT image is supplied the Convolutionary Neural Network (CNN) to classify the plates, whether or not they are readable. After classification the license plate is recognized using Optical Character Recognition. The main purpose of this paper is to identify with maximum efficiency various plate formats and fonts of different state license plates.

Keywords*:* License Plate Recognition, Random Sample Consensus, Successive Mean Quantization Transform, Convolutional Neural Network, Optical Character Recognition.

1. Introduction

Increasing the number of vehicles exponentially includes the use of license plate recognition to preserve vehicle information. In the last few years, the number of vehicles is continuously higher than ever, the traffic conditions are for overpopulation and social needs, the use of cars has decreased, which put tremendous pressure on the environment and the climate.Vehicles play important role in transportation due been increasing day by day. Thus automobile regulation has become a big concern. Automobile plate detection and identification occurs in a wide range of applications, involving roadway car tracking, traffic offense tracking, traffic control, carjacking warning systems, journey time assessment, journey time calculation, road-based car activation, minor crime violation replication, and monitoring implementations. Registration number is really the only trusted automobile identification throughout the ITS. Smart transportation system seems to be a method for handling transport in live time, precision or performance.

The License plate region is localized using the Random Sample Consensus Algorithm [1],[11]. The Successive Mean Quantization Transform is extended to the identified area as an incremental emphasis on both the information in a picture [2],[3]. The SMQT images is fed to the Convolutional Neural Network to classify the localized region whether it is readable or not. [2],[5]. An Optical Character Recognition is used to identify the defined area. It is the mechanical or electronic conversion of printed / printed text images into text encoded on a machine. OCR analyses each section of the picture and seeks to decide whether the black and white dots depict an unique letter or number. The main goal is to identify the Licence plate with specific plate design and high performance fonts.

2. License Plate Recognition

Localized license plate region using the RANSAC Algorithm is taken as the image input for the Successive Mean Quantization Transform. For classification the SMQT images are applied to the Convolutionary Neural Network (CNN). Using the Optical Character Recognition the classified image is recognized.

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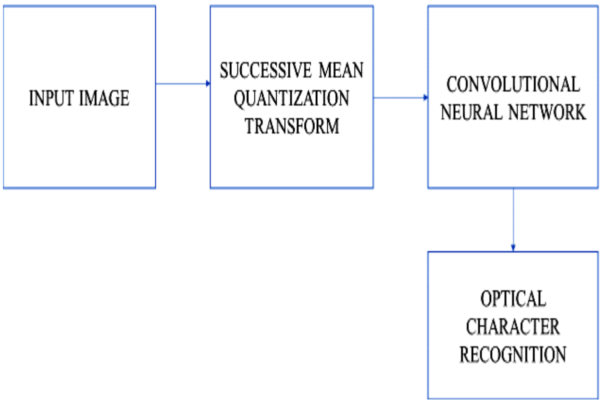

Figure 1: License Plate identification block diagram on SMQT images using CNN and OCR

A. Localization of the license plate

The localization of the license plate is done by using RANSAC (Random Sample Consensus) Algorithm. Localization of vehicle plates is done more accurately based on the Random Sampling Consensus (RANSAC) concept. RANSAC is an iterative algorithm used to fit into a collection of observed data a robust mathematical model. This approach disregards outliers and seeks the best model for the rest of the data given. RANSAC's main use in the field of machine vision is in stereo vision, and specifically in discovering the Fundamental Matrix.

The steps for localizing license plate region using RANSAC Algorithm.

Phase 1: Choose an initial random subset of data called inliers. Phase 2: The collection of inliers is equipped with a pattern. Phase 3: Check all other data against the installed model. Phase 4: The points which match the model are considered as part of the set of consensus.

RANSAC is an outlier detection method. The Location determination problem can be solved by this algorithm.

B. Successive Mean Quantization Transform

Successive Mean Quantization Transform (SMQT) optimization is a non-linear conversion exposing the entity or database model. The algorithm when applied to images “can be seen as a progressive focus on the details in an image”. It will generate a "file" with enhanced data. The algorithm gradually swoops in on the image particulars and exposes details initially concealed by the blackness. In an image each element of the vector representing the intensity of the corresponding pixel.

The phases involved in implementing the SMQT algorithm are:

Phase 1: Calculate the vector mean

Phase 2: divide the vector into two, leaving the numbers in the left half that are less or equal to the mean value, and the numbers in the right half that are greater.

Phase 3: For each value the code will be generated. The values that are below or equal to the mean value get a 0 in their code and the numbers that are greater than the median value get a 1 (this is binary).

Phase 4: All resulting vectors are now divided independently, in a sequential fashion. Each one of these two variables is further divided into two additional vectors and a second bit of code is applied to each based on the wit of their comparison.

Phase 5: The algorithm is repeated recursively.

Mean Quantization Units (MQU) is Successive Mean Quantization Transform's basic building block. The amount (L) in the SMQT represents the number of bits used to define the image that was translated. Similar to many specialized enhancement methods, SMQT has less numerical methods and less adaptations. SMQT on the local area will provide disrespectful lighting and camera functionality. For certain specified stage, entire local patterns consisting of the same structure may result in the similar SMQT features.

C. Progressive Neural Network

CNN is a type of Deep, feeds forwarding neural network that has been successfully implemented to the study of Visual Imagery. Neural Network is a system of interconnected artificial neurons that exchanges messages between them. CNN uses 5 to 25 distinct image recognition levels. CNN comprises of more convolutionary layers often with a sub-sampling layer accompanied by one or more fully connected layers. CNN's connections and parameters are much lower compared to standard feed forward neural networks with similarly sized layers. Notwithstanding their local architecture's relative performance, they were still incredibly expensive to apply to elevated-resolution images on a large scale. Various layers for the construction of Convents are

- Convolution Membrane
- RELU Membrane
- Pooling Membrane
- Fully Linked Membrane

A recently developed regularization method called dropout was used to reduce over fitting in fully connected layers. Take the weight as a 2D matrix to maintain spatial structure in both horizontal and vertical direction, bringing pixels together during both vertically and horizontally path. Taking weight movement both horizontally and vertically, the output is one pixel less in both vertically and horizontally path. Weight Matrix separates image characteristics, it functions like that of a filter on an image that selects particular information from the matrix of the original image. The mixture of weight could be separating edges of a different color or blurring the unwanted noise. The picture size continues to decrease as we increase the stride weight.

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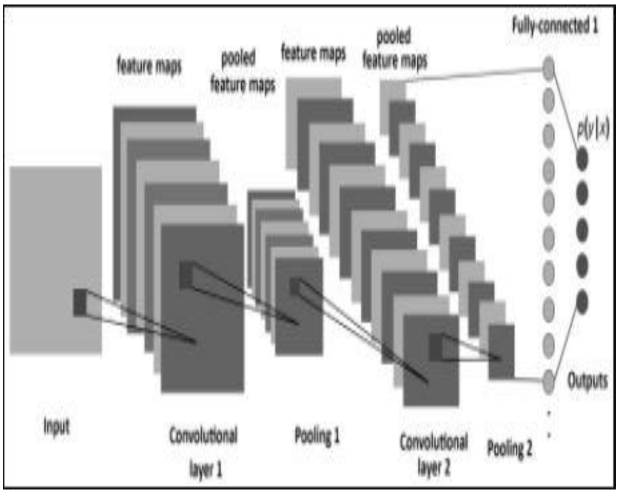

Figure 2: Convolutional Neural Network Architecture

1. Convolutional Membrane

Convolutional Layer is the first layer of CNN. Extracts numerous input traits. First Convolutionary layer removes low level characteristics such as borders, curves, and corners. Lower convolutionary layer excerpts features of a high level. Increasing kernel moved from left to right, one element at a time, starting at the top left corner of data. Upon reaching the top right corner, the kernel moves one part in downward direction until it reaches the lower right corner. Filters (Feature Identifier) are made to slide over the input image where filter is sometimes called called neuron or kernel. The local region covered by that filter is called receptive field Filters are also a collection of numbers, the weights or parameters are called numbers. Determine the function map by the number of filters used. The Alexnet is used as the Feature extractor in Convolution Layer. It consists of five convolutional layer,60 million parameters and 650,000 neurons.

2. RELU Membrane

Rectified Linear Units consists of most deep learning network use rectified linear units for hidden layer. A linear unit rectified does have the output 0 if the input is below zero. I f the input is greater than zero, the output is equal to input.

$$F(x) = \max(x,0) \quad (1)$$

RELU membrane leaves the size of volume unchanged. To identify likely features on each hidden layers. Component by component functions in every function.

3. Pooling Membrane

Spatially consolidated information is also known to reduce the dimensionality of each map as sub-sampling or down sampling, but retains the most important information. It contributes to a significant reduction of parameters. We need to decrease the number of workable variables when images are too growing. Pack layers between the next convolutionary layer are periodically added. Pooling is made to reduce the spatial image compression. In each depth dimension pooling is done independently (profile remains unchanged).

Two types of pooling,

- Pooling at peak level

Maximum value of four is chosen.

- Average pooling rate

The field selects an average of four values.

The largest element in the corrected function map in the window is called in Max pooling. Max Pooling is the most common type of pooling. In both horizontal and vertical directions, two dimensional matrix pixels together, proportions decreased to significantly decrease the variables. The performance volume is governed by three parameters

- Depth
- Stride
- Zero Padding

i. Depth

The number of filters is equivalent. The initial convolutionary layer uses the raw image, and in the presence of different oriented borders or blobes or colors different neurons along the depth dimension will activate. Neurons that look at the same input field as the column size.

ii. Stride

Dictate the steps that we are using to slide the filter. If the step is 1 then move the filter one pixel at a time. If the stride is 2, filter jumps at the time of two pixels. When we slide around it, it produces less space volume than.

iii. Zero Padding

Pad volume of data with zero borderline. The spatial size of output volume can be controlled.

$$\text{Zero padding } P_n = (F_n-1)/2 \quad (2)$$

If the step is 1, make sure the volume and the direction of the output are the same spatially.

4. Fully linked Membrane

It's CNN's last layer. Softmax activation feature in output layer is used by fully connected layer. The softmax function breaks the output of every unit from 0 to 1. Each output is divided to the degree that the total output is one. In measuring each element of the output, all elements of all the features of the previous layer are used. In order to determine specific results, this layer provides the weight of the last layer of functions. Invariant shift is CNN. The same configuration of weight is used throughout space. The same proportions are used at various places in space in CNN.

$$([W-F_n+2P]/S)+1 \quad (3)$$

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W = input capacity
F = filtration volume
P = padding amount added
Ss= strands amount

The threshold value is set as well as the likelihood is defined as being less than or equal to that threshold value because the license plate is not readable. If the probability is greater than the threshold value classified as readable than the license plate is.

D. Optical Character Recognition

OCR (Optical Character Identification) also known as the Optical Character Reader is a system that provides complete alphanumeric identification at electronic speed of typed or handwritten characters by simply scanning the type. The phrase Intelligent Character Recognition (ICR) has been used more recently to describe the process of analyzing visual data, particularly alphanumeric text. The innovation offers solutions for the comprehensive processing of form and the capture of documents. OCR typically uses an open, scaleable, and workflow-controlled modular structure. This provides the characteristics of identifying shapes, sorting, circa-processing images, and identification. Intelligent Character Recognition (ICR) is really the OCR module that enables hand-written or printed character images to be translated into ASCII data. OCR is sometimes known as ICR.

OCR aims at classifying optical structures that correspond to alphanumeric or other characters. The OCR process involves multiple steps along with scalability, extraction and categorisation of features. Function abstraction from input image for character recognition extract character features of single characters based on their geometrical features. This determines how often simple line sections such as horizontal, vertical, and diagonal are in a given character. Their normalized length and surface to the entire image is used as attributes. A further feature is the number of holes in the image.

3. Experimental Results

The project simulation is performed using MATLAB for various plate formats and fonts of different state license plates. In an input image the license plate region is localized using the RANSAC Algorithm and the details of the localized region is enhanced using the Successive Mean Quantization Transform and the enhanced detailed image is fed to the Convolutional Neural Network to classify the plate region whether it is readable or not. For classification using the CNN Alexnet Convolutional Neural Network tool box must be installed. After classification the license plate is recognized using Optical Character Recognition.

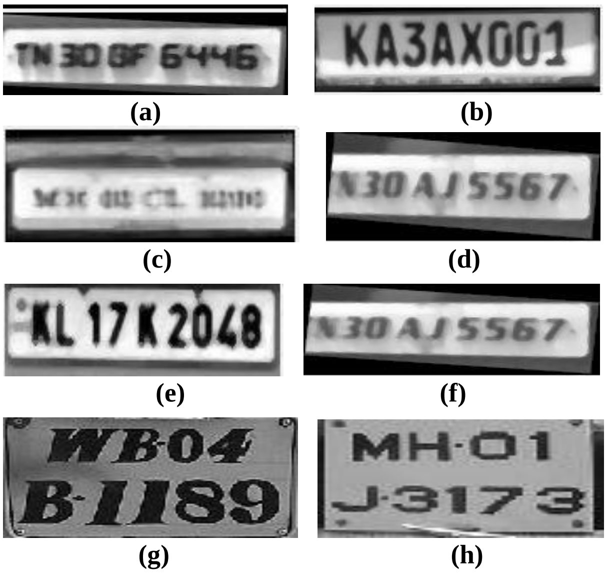
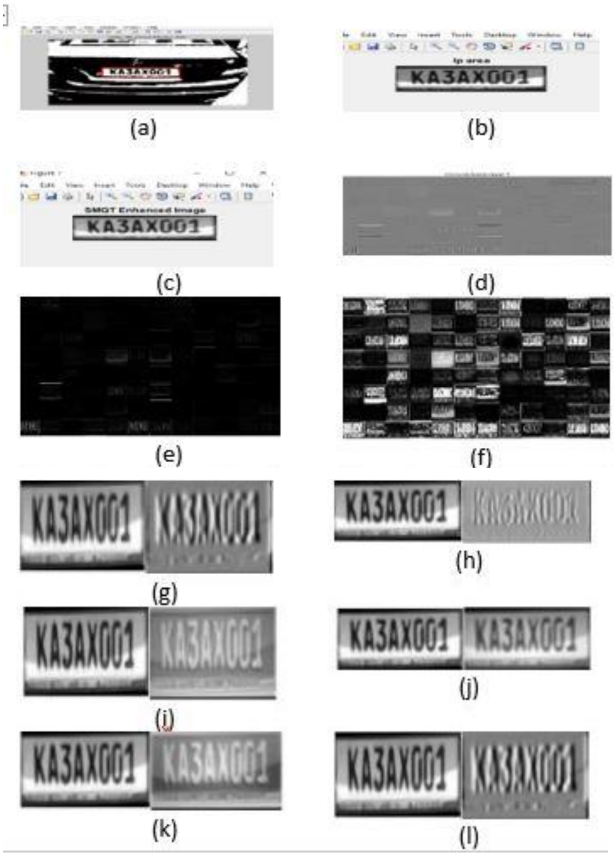


Figure 3: Examples of License plates with different plate Layout and font



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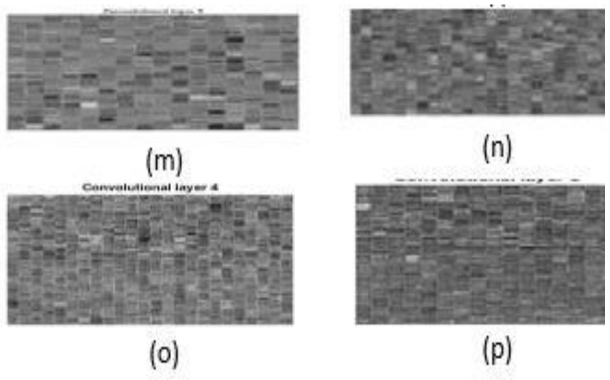

Figure 4: (a) Localized License plate using RANSAC Algorithm; (b) License plate area;(c) SMQT Enhanced image; (d), (e), (f), (g), (h), (i), (j), (k), (l), (m), (n), (o), (p) Convolutional layers output

Figure 5: Recognized License Plate using Optical Character Recognition

Table 1: CNN Accuracy

READABLE	NON READABLE
0.82	0.18

Table 2: Convolutional Layers Output Dimension

LAYER	INPUT	FILTER SIZE	STRIDE	OUTPUT
CONV1	227X227	11X11	4	55X55
CONV2	227X227	5X5	1	223X223
CONV3	227X227	3X3	1	225X225
CONV4	227X227	3X3	1	225X225
CONV5	227X227	3X3	1	225X225

The above outputs of convolutional layers and feature map obtained using the Matlab version 2017b with the installation of Alexnet tool box. The recognition of different plate layout and fonts are recognized using the Optical Character Recognition efficiently.

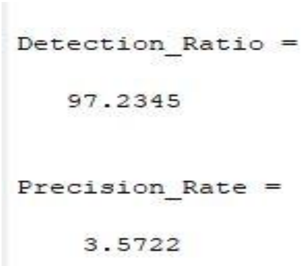

Figure 6: Detection and Precision Values Obtained

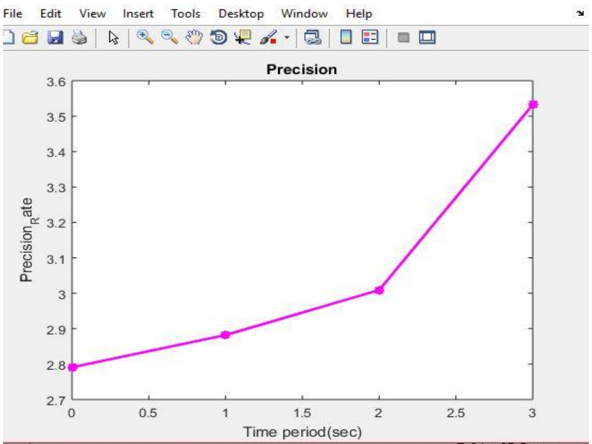

Figure 7: Precision Graph

The detection ratio achieved using the optical character recognition is 97.2% compared to other recognition methods.

4. Conclusion

The identification of the License plate is a significant feature in many fields. The License plate layout and fonts of the License plate characters vary in different states, so in some instances identification is difficult. In many situations, identification of the license plate is necessary, including monitoring or detecting stolen vehicles, data analysis needs for enhancing traffic management, commuter lot management, automatic ticket issuance, toll collection, etc.

Using the RANSAC Algorithm, the license plate is located and the Successive Mean Quantization Transform is extended to the identified zone as a progressive emphasis on the information in a photograph. These images of SMQT were fed to the Convolutionary Neural Network to classify the images as readable or not. Using the Optical Character Recognition, the license plate is recognized after classification.

This work has been simulated using MATLAB 2017a and Alexnet toolbox. Recognition using CNN and

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OCR provides high accuracy compared to other recognition method. The Optical character recognition method provided 97% of detection ratio compared to other recognition methods.

The future development of this work is foreseen, which includes the failure identification of classified non-readable images by training the convolutional neural network

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