Automatic License Plate Recognition(ALPR) Using HTM Cortical Learning Algorithm

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Abstract—**Automatic License Plate Recognition(ALPR) system plays a major role in automatic traffic control and security management, like parking automation, access control, to measure journey time and for law enforcement, etc. This system is designed with a hierarchical temporal memory(HTM) cortical learning algorithm to recognize all the characters that can be found in a license plate. By using HTM spatial pooler component, we could achieve high fault tolerance during recognition.**

Keywords: ***Segmentation, Character recognition, Homomorphic filtering, Connected component analysis, Hierarchical temporal memory - Cortical learning algorithm, Sparse distributed representation.***

I. Introduction

Nowadays the number of vehicles are increasing day by day and so that the need to recognize vehicle license plate is increasing. In recent years, an automatic system that recognize vehicle license plate were introduced. This technology is generally known as Automatic License Plate Recognition(ALPR)[5],[14],[15],[20]. ALPR system applies image processing and character recognition technology to extract the information of vehicle license plate automatically and it can be used for many applications like parking automation, access control, to measure journey time and for law enforcement, etc.

An ALPR system mainly consist of three processes: License plate localization[18],[19], segmentation of characters [10],[17],[24] and recognition of segmented characters [17],[22],[23]. The general framework of the system is given in the Fig 1. Here, license plate can be located by searching license plate characteristics(e.g., high-contrast objects). License plate localization in noisy image that contain other information that may appear as license plates is one of the difficult process of ALPR system. Before segmenting the characters of localized plate, we need some preprocessing steps to remove the noise in the plate. Finally, we can use a character recognition technique to recognize each of the segmented character. Some of the difficulties that need to handle during license plate recognition are given below.

- Poor image resolution

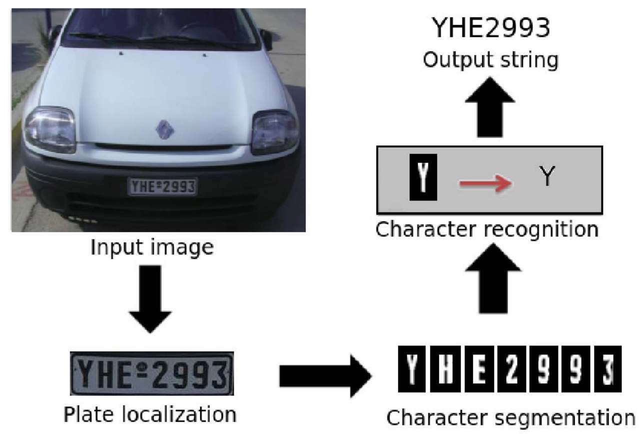

Fig. 1. General framework of ALPR system

- Blurry images
- Lighting and low contrast
- Different types of noise
- Different fonts

The objective of this work is to build an ALPR system by addressing above mentioned difficulties as much as possible. This paper is mainly concentrated on segmentation and character recognition techniques. Here, segmentation is done by using connected component analysis and character recognition is done by using HTM(Hierarchical Temporal Memory) cortical learning algorithm[9]. HTM cortical learning algorithm model the neocortex of the brain. Neocortex is an important part of our brain that uses same algorithm to learn different modalities like audition and vision, etc.

II. Implementation

A. Segmentation

Here, the input is a localized license plate. The following are the major preprocessing steps that we need to do for effective segmentation.

- Homomorphic filtering

- Binarization
- Dilation
- Clear off region with small area

1) Homomorphic filtering: [4]

Homomorphic Filtering is doing to normalize the brightness of the image which helps to reduce noise due to shadow. The block diagram of homomorphic filtering is given in Fig 2. To

Fig. 2. Block diagram of homomorphic filtering

separate the image illumination and reflection components, this filtering approach first take logarithm operation on each pixel. Then, we can use a high pass filter on it. Here, a gaussian filter is used as high pass filter. Finally, taking exponential to enhance the resulting image. Example for homomorphic filtering applied on a license plate with a shadow is given in Fig 3.

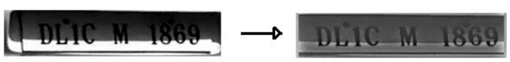

Fig. 3. Result of homomorphic filtering

2) Binarization: Here, thresholding is employed for binarization on homomorphic filtered image. The pixel value less than 72 is mapped to 0 and greater than 72 is mapped to 1.

3) Dilation: Dilation is a morphological operation. Here, a pixel in the original image will be considered as 1 if atleast one pixel under the kernal is 1. Dilation is doing only when the thickness of characters in the plate is less than or equal to 3 pixels. It will increase white region in the image.

4) Clear off region with small area: Final step of preprocessing is the removal of small region in a plate.

An example of preprocessing applied on a sample license plate is given in Fig 4.

Finally segmentation is doing by using connected component analysis(CCA) [20]. In this method, the preprocessed image is scanned and groups its pixels into components based on pixel connectivity. Here, all pixels in a connected component share similar pixel intensity values and are in some way connected with each other. Once all the groups have been determined, each pixel is labeled with a color according to the component it was assigned to.

B. Character Recognition

Architecture of character recognition is given in Fig 6. This system uses *Hierarchical Temporal Memory*(HTM) spatial pooler to recognize the characters more accurately and efficiently. Input to HTM is a binary vaector. Hence, the first step is to build a binary vector corresponding to the input image by the help of an Image Sensor. Image Sensor first convert an input image to a gray scale image. Then, a binary

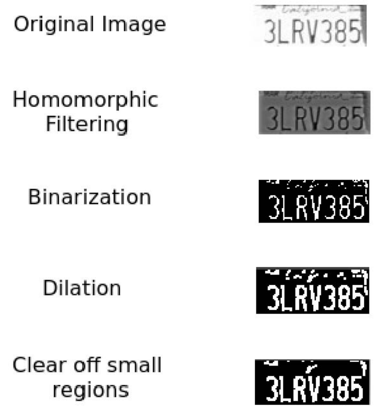

Fig. 4. Preprocessing steps

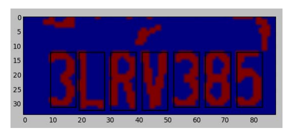

Fig. 5. Segmentation by using CCA

vector is created by the use of thresholding. Resulting vector is passed to HTM. The output of HTM is a *Sparse Distributed Representation*(SDR). Finally, a *K-Nearest Neighbors*(KNN) classifier is trained by using SDR from HTM spatial pooler output and Category of characters from Image sensor output.

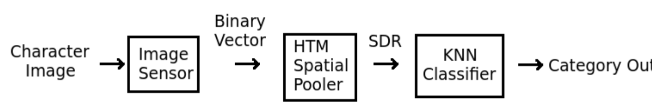

Fig. 6. Character recognition architecture

1) Hierarchical Temporal Memory(HTM): HTM [6],[8],[9] is a type of neural network. Because, as a definition of neural network, anything that model a neocortex is a neural network. HTM mainly consist of two stages of operations - *spatial pooling* and *temporal pooling*. Spatial pooler learn and represent the spatial patterns and temporal pooler learn and represent the sequence of those patterns. HTM mainly have two versions of algorithms- *Zeta-1* [8] and *Cortical learning algorithm*(CLA) [9] . CLA has entirely different algorithm and representation when compared with Zeta-1. Here, we are using CLA. Because, it implement cortical function at more granular and biologically detailed level of abstraction. So, first we can discuss this model by comparing the functions of neocortex. Human neocortex is a sheet of neural tissue. It is divided into several regions. Some regions are related to vision, others to audition and others to languages, etc. These region are logically linked together in a hierarchy. Physical characteristics of the different regions look similar. Each region consist of several columns of cells(neurons). When we receive some sensory information, only some cells becomes active. If we receive time related sequence of input, temporal memory store the sequence by learning the change in activation of different cells. Here, we are using CLA for character recognition purpose. It do not feed time related information. So, we only need the process of spatial pooling [11]. It is a process of forming a sparse distributed representation(SDR). SDR is the language of HTM. It indicates whether a neuron is on or off. The main advantages of SDR is given below.

- Memory efficient
- High fault tolerance
- Preserve semantic similarity among inputs.

HTM spatial pooling can be spilt into three distinct phases.

- Compute the overlap with the current input for each column.
- Compute the winning columns after inhibition.
- Update synapse permanence.

Algorithm 1 Algorithm for HTM Spatial Pooling

Input: *a binary vector consisting of a fixed number of bits*
Output: *SDR*

- Phase 1
    1) For c in columns,
        a) overlap(c)=0
        b) for s in connectedSynapses(c)
            i) overlap(c)=overlap(c)+number of connected synapses with active inputs
        c) if overlap(c) $<$ minOverlap then
            i) overlap(c)=0
        d) else,
            i) overlap(c)=overlap(c)*boost(c)
- Phase 2
    1) if Overlap(c) $>$ Overlap score of N^{th} highest column within c's inhibition radius,
        a) c will be a winner.
- Phase 3
    1) for c in activeColumns
        a) for s in potentialSynapses(c)
            i) If synapse(c) is active,
                A) permanence = permanence + increment value
                B) permanence = min(1, permanence)
            ii) else,
                A) permanence = permanence - decrement value
                B) permanence = max(0, permanence)

Biological neurons are information carrying cells in the brain. Here, every neurons are connected with different dendrites and inputs are received via synapses which are aligned along these dendrites. There are mainly two types of dendrites - *proximal* and *distal dendrites*. Proximal dendrites are closest to the cell body. Feed forward connections to a region of neocortex is connected to these dendrites. Distal dendrites are farther from the cell body and are connected to the cell body via other dendritic branches. This system only contain the feed forward connections. Here, learning involves strengthening and wakening the effect of synapses. In HTM, this effect can be represented by a weight called permanence. Before to start, we need to initialize permanence of each synapse by assigning random permanence value. The pseudo code for HTM spatial pooling is given in Algorithm 1.

In phase 1, a boost factor is used to calculate overlap score of columns. There is a constant competition between columns. So, boost factor is used to avoid the situation where some cells never win in the competition with neighboring cells. The second phase determine the winning columns after inhibition. Here, N is a parameter called local area density which control the number of columns after inhibition. In this implementation, we are using 1024 columns and 2% of these columns as local area density. Phase 3 is a learning phase. Here permanence values of synapses are updated. But, in this implementation, learning is disabled. Because, during learning, the receptive field of columns are changing due to this permanence update. Here we need a constant receptive field forever.

The main advantage of using HTM spatial pooler is the sparsity. We can efficiently store and represent the input vector of size 1024 as a vector of size 21(2% of 1024) when using HTM spatial pooler(Fig.7)

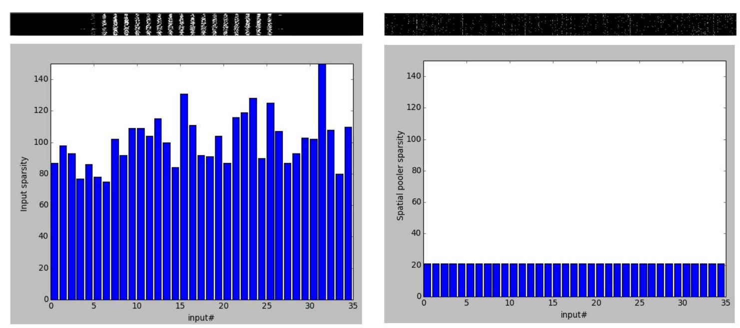

Fig. 7. HTM spatial pooler forms SDRs with fixed sparsity

Finally a KNN classifier is trained using these SDRs.

III. Result and Analysis

The accuracy of this system is evaluated by using 80 sample localized plates. The results are given below.

TABLE I

Operation	Number of correct detection	Accuracy
Segmentation	75	93.75%
Character Recognition	72	96%

Character recognition system is trained by using a collection of characters with different fonts. The fault tolerance of this recognition system is examined by analysing result on training set by adding some salt & pepper noise. It is given in Fig 8.

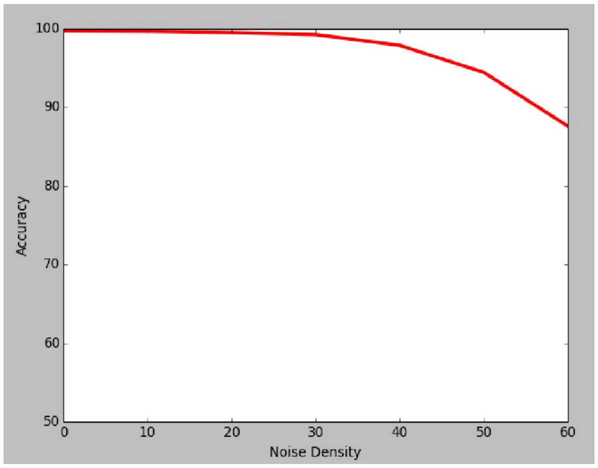

Fig. 8. Fault tolerance of the system

Comparison of HTM-CLA with other character recognition systems by using MNIST dataset is given in Table 1.

TABLE II
COMPARISON OF HTM-CLA WITH OTHER RECOGNITION SYSTEMS

Method used	Recognition Accuracy
HTM-CLA	95.35%
Artificial Neural Network(ANN)	93.3 %
Linear Support Vector Machine(SVM)	93.16 %
KNN	81.7 %

IV. CONCLUSION AND FUTURE WORKS

In this paper, we developed an automatic license plate recognition system based on CCA and HTM-CLA. This system have an advantage of high fault tolerance and memory efficiency. Here, HTM helps to convert each input vector of size 1024 into an SDR of size 21. But, this system only use the concept of spatial pooling. Hence, as our future work, a character recognition system that use all the concept(both spatial and temporal pooler) can be implemented.

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