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License Plate Recognition System

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Abstract: --Vehicle license plate recognition (LPR) technique plays an important role in automated systems for real time traffic management and surveillance. A number of approaches have been proposed for this intelligent transportation systems including road traffic monitoring, parking lots access control, and automated payment on high ways. In this paper, the capability of California license plate recognition is improved by integrating a variety of methods, and the problems such as locating the license, segmenting license plate characters and recognizing characters are resolved. Through a number of license plate image processing, the results show that the license plate recognition method based on Matlab is successful and efficient. The main approach used in the paper is color clustering and neural network, and the accuracy is high up to 92.5%.

Keywords: License plate recognition; Color clustering; K-means; Artificial neural network

1. Introduction

The Automatic Number Plate Recognition (ANPR) was invented in 1976 at the Police Scientific Development Branch in the UK. However, it gained much interest during the last decade along with the improvement of digital camera and the increase in computational capacity [1]. The background of the car image is complicated, and locating the LP region is the key to the automated system. There have been lots of literature about recognition of LPs in Indian, Iran, Germany, China, Australia, etc. However, LP in different countries have different features, and not all of the methods can be applicable for California license plate recognition. The purpose of the paper is to demonstrate the practical approach for California LP recognition. The three components of the LPR algorithms are generally composed of the following three processing steps: 1) location of the license plate region; 2) segmentation of the plate characters; and 3) recognition of each character [2]. The second part of the paper presents the image processing theory and some approaches related to LPR, and the third and fourth parts present how the k-means algorithm and artificial neural network are implemented to achieve the goal of recognition. And the last part is about the experiment evaluation, conclusion and future work.

2. Review of Related Techniques

2.1. LP location detection

To locate the license plate accurately is to find an algorithm to select the area that presents the maximum local contrast that possibly corresponds to the rectangle that contains the LP. As far as the LP location detection is concerned, the approaches generally fall into three main categories, binary image processing, gray or color processing and machine learning algorithms. However, the boundaries between subcategories are not always unambiguous.[3] The approach proposed in this paper is based on color processing.

Edge statistics and mathematical morphology featured very good results in extraction of the plate region. They are based on the property that the brightness change in the plate region is more remarkable and more frequent than otherwise. The Sobel edge detector is also called Sobel operator which widely used in image processing and computer vision. A disadvantage is that edge-based methods alone can hardly be applied to complex images, since they are too sensitive to unwanted edges, which may also show high edge magnitude or variance. [4]

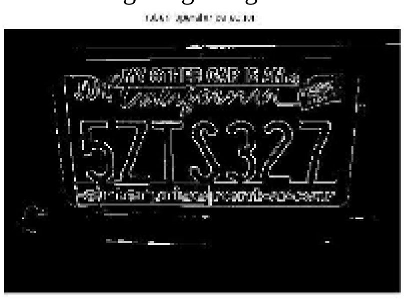

Figure 1. Edge detection

Gray-level processing method includes sliding concentric windows (SCW), Gabor filters, Hough transform, wavelet transform, generalized symmetry transform (GST). An enhanced color-texture-based method for detecting LPs in images was presented in . The authors focus their attention on a support vector machine (SVM)-based approach that extended previous work for texture classification and on the continuous adaptive mean shift (CAMShift) algorithm.

Genetic Programming (GP), and genetic algorithms (GAs) were also implemented for the task of LP location. The higher requirement in terms of computing resources with respect to GAs and the higher complexity of the decoding process.

2.2. LP segmentation

Exploit vertical and horizontal projections of the pixels is the most common and simplest one for character segmentation. The idea is to add up image columns or rows and obtain a projection. It is used to find the upper and lower bound of the license plate. In this way, the unnecessary boundary can be completely removed. When all values along all lines in the horizontal direction are computed, the horizontal projection histogram is obtained. The mean value is used as the threshold to decide the upper and lower bounds. [5]

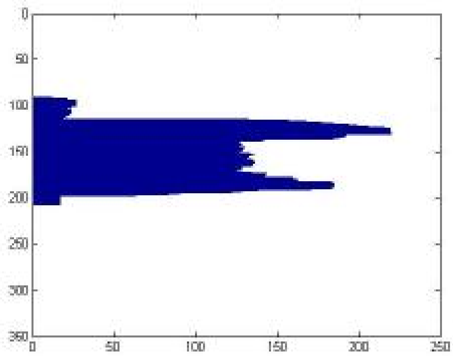

Figure 2. Horizontal projection

After the area bounded by the upper and lower bounds of a license plate is found, the areas above the upper bound and below the lower bound are removed. When all values along all lines in the vertical direction are computed, the vertical projection histogram is obtained. Based on the results of vertical projection, each license plate is separated into blocks horizontally by the zero points in the projection histogram. The average widths of these blocks are used as the estimated width of characters.

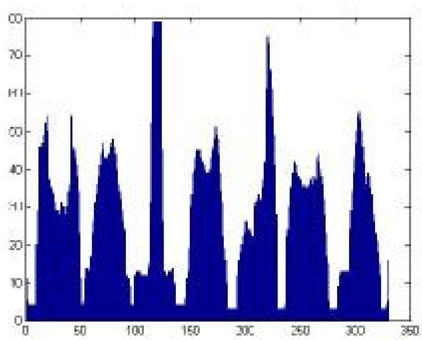

Figure 3. Vertical projection

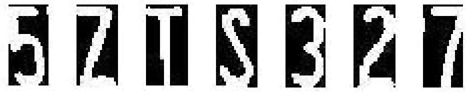

Figure 4. Segmentation of LP

2.3. LP recognition

2.3.1. Template matching

The process involves the use of a database of characters or templates.

Figure 5. Database of characters

Figure 6. Recognition result

Through experiments, template matching approach is impressively accurate and relevantly fast. There have been a large number of character recognition techniques reported. They include genetic algorithms , artificial neural networks , fuzzy c-means, support vector machine, Markov processes, and finite automata.

2.3.2. Artificial neuron networks

Although artificial neural networks have gained a lot of popularity in recent years, early studies of neural networks go back to the 1940s when Warren McCulloch and Walter Pitt first described how neurons could work. However, in the decades that followed the first implementation of the McCulloch-Pitt model, many researchers and machine learning practitioners slowly began to lose interest in neural networks since no one had a good solution for training a neural network with multiple layers. Eventually, interest in neural networks was rekindled in 1986 when D.E. Rumelhart, G.E. Hinton, and R.J. Williams were involved in the discovery and popularization of the backpropagation algorithm to train neural networks more efficiently.

3. K-means Clustering Algorithm for LP Location

Based on color clustering, the similar color in the image can be clustered, thus the blue characters in the image can be extracted. The LP location is eventually determined from the candidates through morphological operations and the filtering of length to width ratio of the license characters.

3.1. Color space

Labcolor spaceis a 3-axis color system with dimension L for lightness and a and b for the color dimensions. The Lab color space is the most exact means of representing color and is device independent. This accuracy and portability makes it suitable in a number of different industries such as printing, automotive, textiles, and plastics.[6] . There are also other ways to represent color, for example, RGB and HSV. RGB (Red, Green, Blue) describes what kind of light needs to be emitted to produce a given color. RGB stores individual values for red, green and blue. It means that different proportions of Red, Blue and Green light can be used to produce color. The RGB color model was created specifically for display purposes (display screens, projectors etc). Light is added together to create form from darkness. RGB is not a color space, it is a color model. HSV(hue, saturation, value), also known as HSB (hue, saturation, brightness), is often used by artists because it is often more natural to think about a color in terms of hue and saturation than in terms of additive or subtractive color components. For certain applications, we require a better representative model of color and hence, we have the HSV space. The intention of CIELAB (or L*a*b* or Lab) is to produce a color space that is more perceptually linear than other color spaces. Perceptually linear means that a change of the same amount in a color value should produce a change of about the same visual importance. The a axis extends from green (-a) to red (+a) and the b axis from blue (-b) to yellow (+b). The brightness (L) increases from the bottom to the top of the three-dimensional model.

3.2. LP detection algorithm

The basic idea of detection algorithm is to efficiently remove the non-character area. Clustering is a technique that allows to find groups of similar objects, objects that are more related to each other than to objects in other groups [7]. K-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster [3]. Given a set of observations $(x1, x2, ..., xn)$, where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into $k \ (\le n)$ sets $S = \{S1, S2, ..., SK\}$ so as to minimize the within-cluster sum of squares (WCSS) (sum of distance functions of each point in the cluster to the K center). In other words, its objective is to find:

$$\frac{\arg\min}{S} \sum_{i=1}^{k} \sum_{x \in Si} \left\| X - m_i \right\|^2 \quad (1)$$

where m_i is the mean of points in S_i You can classify each pixel in the image by calculating the Euclidean distance between that pixel and each color marker. The smallest distance will tell you that the pixel most closely matches that color marker. For example, if the distance between a pixel and the red color marker is the smallest, then the pixel would be labeled as a red pixel. Thus, the goal is to group the samples based on their feature similarities, which can be achieved using the k-means algorithm that can be summarized by the following four steps: 1) randomly pick k centroids from the sample points as initial cluster centers. 2) Assign each sample to the nearest centroid $m^{(j)}$, $j\{1,...,k)\}$. 3) Move the centroids to the center of the samples that were assigned to it. 4) Repeat the steps 2 and 3 until the cluster assignment do not change or a user-defined tolerance or a maximum number of iterations is reached [8].

The k-means clustering can be applied to data in higher dimensions, and the dataset here is tow-dimensional. The number of clusters k is set to 5 in this case, specifying the number of clusters a priori is one of the limitations of k-means. By default, k-means uses the squared Euclidean distance measure and the k-means++ algorithm for cluster center initialization.

3.3. Post-processing

3.3.1. Binary image

The algorithm to convert RGB color map to grayscale is by eliminating the hue and saturation information while retaining the luminance. Ostu's global thresholding method is used to convert the gray scale image to binary image.[9] Based on a very simple idea that to find the threshold that minimizes the weighted within-class variance. This turns out to be the same as maximizing the between-class variance. The weighted sum of variances of the two classes:

$$s_w^2(t) = w_o(t) s_0^2(t) + w_1(t) s_1^2(t) \quad (2)$$

Weights $wo,1$ are the probabilities of the two classes separated by a threshold t and s_0^2 are variances of these two classes. The class probability $W_{0,1}(t)$ is computed from the L histograms:

$$w_0(t)=\sum_{i=o}^{t-1} p(i) \tag{3}$$

$$w_1(t)=\sum_{i=t}^{L-1} p(i) \tag{4}$$

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$s_b^2(t)=s^2-s_w^2(t)=w_o(m_o-m_T) \tag{5}$$

which is expressed in terms of class probabilities w and class means m, while the class mean $m_{0,1,T}(t)$ is:

$$m_0(t)=\sum_{i=o}^{t-1} ip(i)/w_0 \tag{6}$$

$$m_1(t)=\sum_{i=n}^{L-1} ip(i)/w_1 \tag{7}$$

3.3.2. Morphological operation

Morphological operations apply a structuring element to an input image, creating an output image of the same size. The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. [10]. The basic effect of an opening is somewhat like erosion in that it tends to remove some of the foreground (bright) pixels from the edges of regions of foreground pixels. Closing is similar in some ways to dilation in that it tends to enlarge the boundaries of foreground (bright) regions in an image (and shrink background color holes in such regions), but it is less destructive of the original boundary shape.

3.3.3. Connected component analysis

Characters in the license plate will become more significant after morphological operation, yet there may be other disruption regions in the image, therefore connected component analysis is used to overcome the problem. Connected component analysis is a vital technique in binary image processing that scans an already binarized image and labels its pixels into components based on pixel connectivity. Once all groups of pixels have been determined, each pixel is labeled with a value according to the component to which was assigned. Relatively simple to implement and understand, the two-pass algorithm iterates through 2-dimensional, binary data. The algorithmmakes two passes over the image: the first pass to assign temporary labels and record equivalences and the second pass to replace each temporary label by the smallest label of its equivalence class. Each of the characters in the license plate is a connected component.Further filter the candidates. Generally, the characters on the license plate is between 0.4-0.5. Also, if the width is less than 50 or the length is less than 80, it is not considered as the character. At this time the license plate characters can be completely separated from other disruptions. License plate segmentation is an important part and can influence greatly the following recognition. If the characters cannot be separated correctly, there is no way to make the automated system successful afterwards.

4. Artificial Neural Networks

Template matching techniques were used for license plate recognition but these were sensitive to noise, so neural networks are used for recognition. Neural network has the capability of learning. Neural networks, with their remarkable ability to drive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques.[11] Artificial Neural Network resembles human brain in following ways: 1) It requires knowledge through learning. 2) Artificial Neural Artificial neural networks are generally presented as systems of interconnected "neurons" which exchange messages between each other. Network knowledge is stored within interneuron connection strengths known as synaptic weights.

Learning of neural networks is done by loading targets and features extracted from license plate characters.

The preceding figure illustrates how the perceptron receives the input of a sample x and combines them with the weights w to compute the net input. The net input is then passed on to the activation function, which generates a binary output -1 or +1--the predicted class label of the sample. During the learning phase, this output is used to calculate the error of the prediction and update the weights. $y(x)=j\left(\sum wi*xi\right)(1)$ x is a neuron with n input dendrites $x(0),x(1),.......x(n)$ and one output a on $y(x)$ and where $w(0)$, $w(1),......w(n)$ are weights determining how much the inputs should be weighted and φ is an activation function that weights how powerful the output artificial neuron should mimic a real neuron. Connect multiple single neurons to form a multi-layer feedforward neural network. Artificial neural network consists of input layer, hidden layer and output layer. The units in the hidden layer are fully connected to the input layer, and the output layer is fully connected to the hidden layer, respectively. The nonlinear activation functions in this multi-layer perceptron (MLP) model is the sigmoid activation function. Sigmoid function refers to the special case of the logistic function shown in the following figure and defined by the formula

$$S(t)=\frac{1}{1+e^{-t.}} \tag{8}$$

A sigmoid function is a mathematical function having an "S" shape (sigmoid curve).

Firstly, training data is fed into the input layer. It is propagated to both the hidden layer and the output layer. This process is called the forward pass. Each node in the input layer, hidden layer and output layer calculates and adjusts the appropriate weight between nodes and generate output value of the resulting sum. After that the actual output values will be compared with the target output values. Back propagation is a supervised form of learning[12].

The error signal between desired output and actual output is being propagated in backward direction from output to hidden layer and then to input layer in order to train the network. The network will iterate over many cycles until the error is acceptable. After the training phase is done, the trained network is ready to use for any new input data. Since the input image is 26*26 pixels, it can be normalized to a 512*1 matrix. Information is thus fed to a neural network with 512 (one for each pixel) neurons in input layer, one hidden layer with 80 neurons and finally the output layer with 36 neurons, with each neuron corresponds to a number from 0 to 9 or character from A to Z. The network has to be trained for many training cycles in order to reach a good performance.

Table 1. Multilayered neural networks recognition details

Topology	Performance	Output classes
16-20-9	95%	9 numbers
24-15-36	98.5%	26letters+10 numerals
209-104-36	95%	26 letters+10 numerals
15-10-8	96%	Binary ASCII code of 36 characters
108-50-35	95%	25 letters +10 numerals

5. Experiment Evaluation

Two main issues are processing time and color-based scheme. Color based approach may fail at detecting various license plates with varying colors. Though color processing shows better performance, it still has difficulties recognizing a car image if the image has many similar parts of color values to a plate region, however, this situation rarely happens.

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