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Application of Gaussian-Hermite Moments in License

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1. Introduction

In recent years, many researches on intelligent transportation systems (ITS) have been reported. ITSs are made up of 16 types of technology-based systems divided into intelligent infrastructure systems and intelligent vehicle systems. As one form of ITS technology, vehicle license plate recognition (VLPR) is one of important techniques that can be used for the identification of vehicles all over the world. There are many applications such as entrance admission, security, parking control, airport or harbor cargo control, road traffic control, speed control, toll gate automation and so on. LPR, as a means of vehicle identification, may be further exploited in various ways such as vehicle model identification, under-vehicle surveillance, speed estimation, and intelligent traffic management. Character recognition is an essential and important step in an ALPR system, which influences the overall accuracy and processing speed of the whole system significantly (Jia, 2007 & Christos-Nikolaos et al., 2008).

However, few researches have been done for recognition of car plate character. Neural network method has been employed to recognize car plate characters. The method can achieve promising performance if the quality of the given car plate image is well. However, the quality of image taken for car plates is not always well. This is due to the operating conditions (e.g. dust on the car plates) and distortion or degraded because of poor photographical environment. Experiments have shown that it is difficult to achieve high car plate recognition rates only by extracting features from character are fed into neural network method (Rosenfeld, 1969, Huang et al., 2008).

Moments, such as geometric moments and orthogonal moments, are widely used in pattern recognition, image processing, computer vision and multiresolution analysis (Shen, 1997, 2000; Wu & Shen, 2004; Wang et al., 2004, 2007;). We present in this paper a study on Gaussian-Hermite moments (GHMs), their calculation, properties, application and so forth.

In this paper, we at first the plate image by preprocessing algorithms (skew corrected, character segmentation, binary image and normalized) before recognition. Then, we propose the GHMs features as the input vector of BP neural network. Our analysis shows orthogonal moment's base functions of different orders having different number of zero crossings and very different shapes, therefore they can better reflect image features based on different modes, which is very interesting for pattern analysis, shape classification, and detection of the moving objects. Moreover, the base functions of GHMs are much more smoothed; are thus less sensitive to noise and avoid the artifacts introduced by window

function's discontinuity (Fernandez-Garcia, & Medina-Carnicer 2004). Our method can have potential applications in video retrieval, and in other related areas of video information processing.

This paper is organized as follows. First, Section II introduces methods for image preprocessing. Section III presents the orthogonal Gaussian-Hermite moments and their behaviors in the license plate character image. In Section IV, proposes the GHMs features as the input vector of BP neural network for recognizing characters. Section V shows some experiment results. Finally, conclusions are drawn and with the future work discussed as well.

2. Image preprocessing

2.1 Orientation method for skew correction

The skew correction of license plate is an important step in ALPR. The license plate inclination is determined by the direction of the boundary. In order to find such direction. In our paper (Ma et al., 2009), the license plate image is firstly divided into a set of 5×5 non-overlapping blocks. The local orientation of each block is estimated by gradients [Gx,Gy] of pixels in the block. It may reduce much processing time. Next, the direction histogram which can reveal the overall orientation information in the license plate image is counted. The skew angle of license plate is detected by the local maximum of the direction histogram. This approach can solve the direction detection problem in a very straightforward and robust way under various conditions. Fig. 1 gives some images before and after skew correction.

Original images   Adjusted images

Fig. 1. Corrected license plates

2.2 Segmentation character

This part extracts individual character images from the plate image. The plate window region can contain license surrounding some region that can create resistance in character recognition segment. In order to better extract characters of plate image. We have to remove this unexpected region so that the image only holds the license number. This can be done by a horizontal segmentation and a vertical segmentation on both sides of the number plate. After segmenting horizontally and vertically, the plate image will be as the Fig. 2(c).
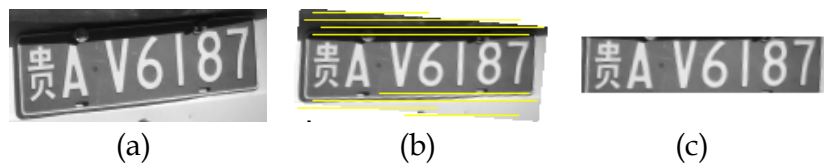
(a) (b) (c)

Fig. 2. Frame removal: (a) Original image; (b) The horizontal cut lines after corrected; (c) Frame removed

Then, calculating for segmentation points by the vertical projection and merging fragments that belong to the same character. The average filter with length s=3 reduce noise. The characters will be extracted from the vertical projection histogram of plate image. The extracted characters are given in Fig. 3.

2.3 Adaptive threshold for image binarization

All the character images are binarized using an anto-adaptive threshold. We propose many iterations algorithm for obtaining the optimal thresholds for segmenting gray scale images. The image background is black (gray value is 0) and the characters are white (gray value is 255).

Given that F(x,y) is the edge image and T is a predefined threshold Tn is a dynamic threshold. The following equation is used to obtain a local optimal threshold value.

$$T = \frac{1}{2}\{\min[F(x,y)] + \max[F(x,y)]\} \tag{1}$$

$$T_n = \frac{1}{2}\left[\frac{1}{M}\sum_{F(x,y) \leq T}\sum F(x,y) + \frac{1}{N}\sum_{F(x,y) > T}\sum F(x,y)\right] \tag{2}$$

where M is number of pixel with its gray value less than T , N is number of pixel with its gray value larger than T.

```
Loop :
if (T ≈ Tn)
        end  loop;
else if | T- Tn | <0.6,
        T=Tn; goto  loop;
end if
```

If the intensity of every pixel value is greater than T, the pixel is set to white; otherwise, it is set to black. The binary image is given in Fig. 3.

2.4 Normalization

Characters segmented from different car plates have different sizes. A linear normalization algorithm is applied to the input image to adjust to a uniform size.In our implementation, character blocks are normalized to a fixed size of 32*16 pixels.Assume the horizontal and vertical projections of the original image F be H and V, respectively. The normalization position (m,n) of (i,j) is obtained by

$$m = \sum_{k=1}^{i} H(k) \times \frac{M}{\sum_{k=1}^{j} H(k)} \tag{3}$$

$$n = \sum_{k=1}^{j} V(k) \times \frac{N}{\sum_{k=1}^{j} V(k)} \tag{4}$$

where m, n is height and width of normalized image.

Before normalization

After normalization

Fig. 3. Character images before (upper) and after(lower) size normalization

3. Gaussian-Hermite moments (GHMs) and their behaviors in plate character

Moments, such as geometric moments and orthogonal moments, are widely used in pattern recognition, image processing, computer vision and multiresolution analysis. However, some moments base functions exhibit a great discontinuity [6] at the window boundary. In order to better represent local characteristics of images, particularly for noisy images, one should use orthogonal moments with a smoothing window function. Taking the well-known Gaussian functions as smoothing kernel, smoothed orthogonal Gaussian-Hermite moments (GHMs) were proposed [7-10]. Moreover, the base functions of GHMs are much more smoothed than other moments, thus less sensitive to noise and avoid the artifacts introduced by window function's discontinuity.

3.1 Gaussian-Hermite Moments

GHMs were proposed by J. Shen[11-12]. Given the Gaussian smoothing function $g(x,\sigma)$ with

$$g(x,\sigma) = (2\pi\sigma^2)^{-1/2} \exp(-x^2 / 2\sigma^2) \tag{5}$$

the nth order smoothed GHMs $M_n(x,S(x))$ of a signal $S(x)$ is defined as

$$M_n(x,S(x)) = \int_{-\infty}^{\infty} B_n(t)S(x+t)dt \qquad n = 0,1,2,... \tag{6}$$

With

$$B_n(t) = g(t,\sigma)P_n(t) \tag{7}$$

Where $P_n(t)$ is a scaled Hermite polynomial function of order n defined by

$$P_n(t) = H_n(t/\sigma) \tag{8}$$

With

$$H_n\left(t/\sigma\right) = \left(-1\right)^n \exp\left(t^2\right)\left(d^n/dt^n\right)\exp\left(-t^2\right) \tag{9}$$

The GHMs can be recursively calculated as follows [10]:

$$M_n\left(x, S^{(m)}(x)\right) = 2(n-1)M_{n-2}\left(x, S^{(m)}(x)\right) + 2\sigma M_{n-1}\left(x, S^{(m+1)}(x)\right) \quad \text{for } m \geq 0 \text{ and } n \geq 2 \tag{10}$$

with

$$M_0\left(x, S^{(m)}(x)\right) = g(x,\sigma) * S^{(m)}(x) \qquad \text{for } m \geq 0 \tag{11}$$

$$M_1\left(x, S^{(m)}(x)\right) = 2\sigma d[g(x,\sigma)]/dx * S^{(m)}(x) \tag{12}$$

and in particular,

$$M_0\left(x, S(x)\right) = g(x,\sigma) * S(x) \tag{13}$$

$$M_1\left(x, S(x)\right) = 2\sigma d[g(x,\sigma) * S(x)]/dx \tag{14}$$

Where

$$S^m\left(x\right) = d^m S(x)/dx^m \tag{15}$$

$$S^0\left(x\right) = S(x) \tag{16}$$

and * denotes the convolution operator.

Now we analyze the spatial domain behavior of smoothed GHMs base functions. Because the nth order Hermite polynomial $H_n(t)$ has n different real roots, the base function of GHMs $g(x,\sigma)H_n(x/\sigma)$ will also have n different real roots. Therefore the base function of the nth order GHMs will change its sign n times. In other words, it consists of n oscillations. So GHMs can well characterize different spatial modes as other orthogonal moments. Fig. 4 shows the spatial behavior of GHMs base functions of different orders.

As to the frequency domain behavior, since Gaussian-Hermite base functions comprise more and more oscillations when the order n is increased, they will thus contain more and more high frequencies. From the spectral analysis viewpoint, the GHMs efficiently separate the signal features in different frequency bands. Fig. 5 shows the Fourier transform amplitude of some base functions of GHMs.
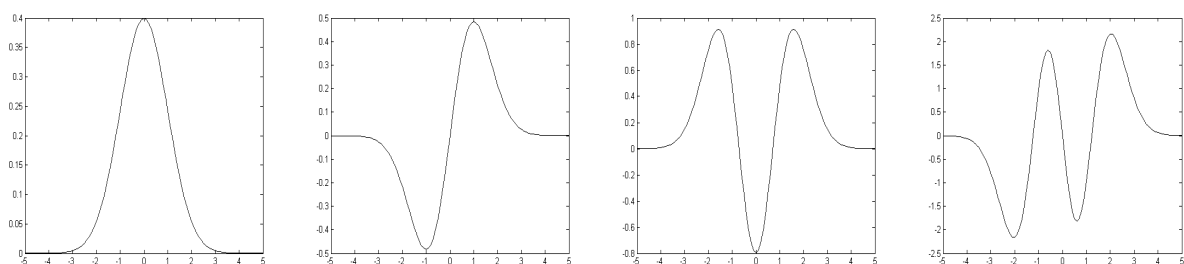

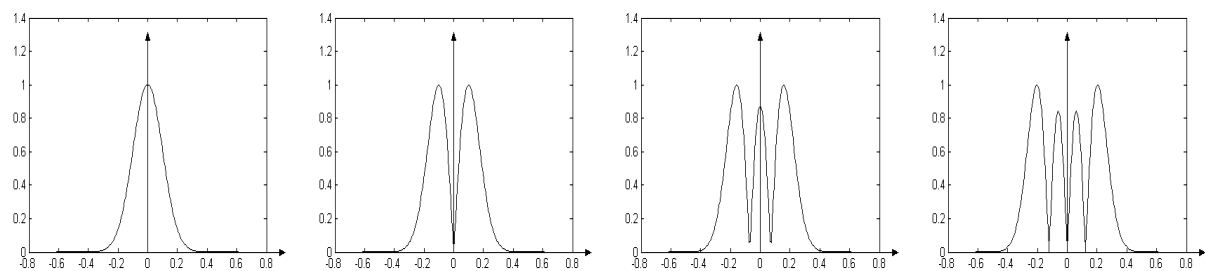Fig. 4. Spatial behavior of 1D GHMs base functions (orders: 0 to 3)

Fig. 5. Frequency behavior of 1D GHMs base functions (orders: 0 to 3)

Moreover, from the recursive calculation of GHMs, we see that these moments are in fact linear combinations of the derivatives of the signal filtered by a Gaussian filter. As is well known, the derivatives have been extensively used for image representation in pattern recognition.

2D orthogonal Gaussian-Hermite moments of order (p,q) of an input image $I(x,y)$ can be defined similarly

$$M_{p,q} = \iint_{-\infty}^{\infty} G(t,v,\sigma) H_{p.q}(t/\sigma, v/\sigma) S(x+t, y+t) dt dv \qquad (17)$$

Where $G(t,v,\sigma)$ is the 2D Gaussian function, and $H_{p.q}(t/\sigma, v/\sigma)$, the scaled 2D Hermite polynomial of order (p,q), with

$$H_{p.q}(t/\sigma, v/\sigma) = H_p(t/\sigma) H_q(v/\sigma) \qquad (18)$$

Obviously, 2D Gaussian-Hermite moments are separable, so the recursive algorithm in 1D cases can be applied for their calculation. Fig. 6 shows the Fourier transform amplitude of a bidimensional GHMs kernels of different orders. We use GHMs to efficiently recognition the character plate image.
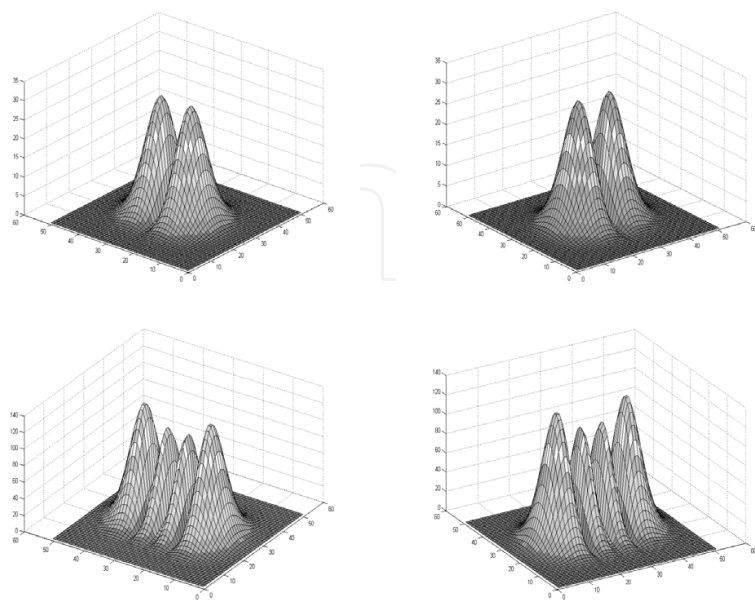

Fig. 6. Frequency behavior of 2D base functions of GHMs (orders: (0,1), (1, 0), (0, 3) and (3, 0))

3.2 Representation of feature vector with of GHMs in license plate character

In order to characterize these features in the license plate character image, we use 231 2D base functions of GHMs of different order (orders: $p + q \leq 20$). The number and the order of GHMs required were empirically determined.

The feature vector with Gaussian-Hermite moments $M_{p,q}$ of license plate character is represented by

$$M = [M_{0,0}, M_{0,1}, M_{0,2}, \dots, M_{0,20}, \quad M_{1,1}, \dots, M_{1,19}, \dots, M_{19,0}, M_{19,1}, \quad M_{20,0}]^{T} \quad (19)$$

4. Character recognition

For the recognition of segmented characters, the Gaussian-Hermite moments features are extracted from each character are lumped into a vector as input of the BP neural network [13,14]. The Bp neural network is a three-layer structure.

4.1 BPNN model

A neural network (NN) is an artificial network model, which emulates the cerebral nerve network in the brain. Characters are recognized using a supervised back propagation neural network (BPNN) classifier (see Fig.7). A BPNN is trained by adjusting the weights of the connections between the nodes of the different layers before the BPNN can be used. The input patterns are fed into the input layer and the error between the expected output and the actual output are propagated backwards through the network such that the weights can be adjusted to minimize the errors. This training procedure is repeated until the error is sufficiently small. When learning of neural network complete, we can used that for recognize character of license plate. A major advantage of BPNN is that a trained network is capable of classifying unknown pattern with little computational effort. In this paper, we use a three-layered BPNN architecture. Fig. 7 shows the three-layered BP neural network architecture.

4.2 Input of BPNN with GHMs features

The Gaussian-Hermite moments feature obtained from license plate character as the input vector of BPNN. We use GHMs feature extraction as our method for character recognition. Since the base functions of GHMs are much more smoothed and thus less sensitive to noise, GHMs could facilitate the recognition of character in noisy image sequences. This method distinguishes characters by their unique features.

The license plate character images is characterized by a vector of Gaussian-Hermite moment Mp+q (in our experiment, σ = 0.6). The order of used moments are of 0th-20th (N = 20).

The character images (including references and noisy images) is then characterized by 231 2D moments of orders (0,0),(0,1),…,(0.20), (1,0), (1,1) ,…, (1,19),…,(20,0).

The number of units in BPNN is shown in Table 1. The three-layered BPNN that contains 231 input units, 120 hidden units. Learning rate was 0.05, and the number of learning cycles was 5000, an error value less than 1.0*10-7, then learning stopped. It has 34 types of characters, including 24 character and 10 numbers, the maximum sample number for training and testing is 200.

The number of units in BPNN

Input layer	231
Hidden layer	120
Output layer	6

Table 1.

We use Network to denote the number and character network. According to the feature of Network, 6 neurons are set. So the output vector is $O=[o_1,o_2,o_3,o_4,o_5,o_6,]$, the expectation output of network is {0,0,0,0,0,0}, {0,0,0,0,0,1}, {0,0,0,0,1,0}, {0,0,0,0,1,1},…, {0,1,1,1,1,1}, {1,0,0,0,0,0}, {1,0,0,0,0,1} corresponds number and character separately.

The number of hidden neurons relates to the input and output unit directly. If the hidden neurons are too few, the network possibly cannot train well, local minimum are more and no robust, it could not distinguish the sample which had not seen before, and the fault tolerance is bad. The increase hidden neurons maybe improve the match precision between the network and the training set, but it will causes the study time too long again, the error is also uncertain the best. The choice of hidden neurons is given according to the empirical formula usually:

$$n = \sqrt{n_1 n_0} + \delta \left(1 \le \delta \le 10\right) \qquad (20)$$

n1, n0 are the number of inputs and the output respectively, so the neural network structure is shown as Fig.7.
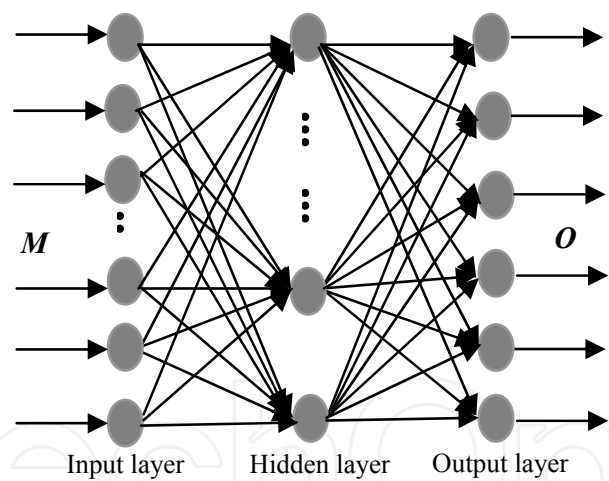

Fig. 7. Three layers BPNN Structure

5. Experimental result

In this section, preliminary experiments for testing the feasibility and robustness of our method are conducted by applying the above-mentioned procedure. One is license plate images which are directly captured by a mobile surveillance system. There are 200 training and testing sample images to be processed using our algorithm. Table 2 shows the results using this set of images.

The testing results using the images in the first category are very encouraging. The average recognition accuracy is 97.93%. Among 200 testing images, only few very poorly focused samples have failed for the number of character training samples is not many. The increase

of training samples would improve recognition accuracy. As a whole, these results are satisfactory enough for the character recognition process.

Correctness Rate (%) / Input of BPNN	Character	Uppercase	Number
proposed feature (Pan et al., 2005)	86.7	89.2	87.4
GHMs feature	98.6	97.4	97.8

Table 2. Experimental results

6. Conclusion and future work

Although significant progress has been made in the last decade, there is still work to be done, as a robust LP recognition system should effectively work for a variety of environmental illumination, plate types/conditions, as well as acquisition parameters. Moreover, most LPR systems focus on the processing of images with one vehicle. Nevertheless, input images may contain more than one vehicle or motorcycles.

In addition, assuming that LP regions are detectable even in very low resolution, an open topic for future research is the readability improvement of LP text using image processing techniques. Research for improving degraded plates has lately been directed to superresolution methods for video sequences or to blurred plate images with promising results.

Though the new method proposed in this paper is still in its stage of a prototype, it has already shown its potential for various implementations. This method can also be used for detecting the moving objects. Our research will be carried on following this track.

7. Acknowledgment

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