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License Plate Recognition Model Research Based on the Multi-Feature Technology

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Abstract

Due to the impact of pollution, environment and so on in actual scene, it is difficult for the traditional single feature recognition model to obtain a higher accuracy of the license plate recognition. The paper proposed a new license plate image recognition model. First, the structural features and gray level features of the license plate, such as the contour and stroke order are extracted. Then, the principal component analysis is used to carry out the fusion, dimensionality reduction and redundancy removal processing for the two kinds of features, and a fuzzy fusion model for differentiated features is introduced to ensure minimal loss for the feature in fusion. Finally, the final result of the license plate image recognition is achieved in accordance with high degree of confidence criterion when the slope interference of the license plate is considered fully. Simulation results show that the license plate image recognition model based on multi-feature combination can solve the problem of the single feature recognition model, improve the accuracy of license plate recognition which is up to 99%. Moreover, the model has a faster recognition speed and can be applied to the actual license plate recognition.

Keywords: *license plate recognition, structural features, grey scale features, principal component analysis*

1. Introduction

With the increase in the number of vehicles, intelligent traffic control plays an increasingly important role in the development process of the transportation industry [1]. Car license plate recognition is an important element in the study of intelligent traffic control, especially in complex environment [2].

Automatic license plate recognition is a classic two-class problems, including license plate image acquisition, the image automatic location, license plates feature extraction separation and license plate recognition. The accuracy and speed of license plate recognition represent the entire performance merits of the automatic license plate recognition system. License plate recognition model is basically based on the structural characteristics of the binary image with advantages of high recognition speed and feature extraction, etc. whose precision is high under normal circumstances [3]. Actually, the license plate photo shoot in a complex environment is different from the actual license plate images, such as the license plate was sludge sheltered, license plate rust caused by long useful life, shooting in non-ideal weather conditions (torrential rain, cloudy, high temperature, and the strong sunshine), and there are even big differences between license plate images shot at night and during the day [4, 5]. Therefore, original license plate conversion with traditional binary model will lead to a serious loss of image information and low recognition accuracy [6]. Later scholars have proposed the gray feature of license plate image can be used to completely reserve the initial information and achieve the automatic license plate recognition [7]. But the feature dimension of the model get is too high and the computational complexity is increased exponentially which makes the recognition time too long cannot meet the real-time intelligent traffic management requirement. In addition, the identify effect is not superior to the structural characteristics of the binary image. Therefore, how to improve the accuracy of license plate recognition remains an open problem-solving [8].

To this end, a license plate image recognition model based on multi-feature combination, which integrates the advantages of both structural feature and grey level feature, is proposed in this paper. First, the structural features and gray level features of the license

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plate, such as the contour and stroke order are extracted. Then, the principal component analysis is used to carry out the fusion, dimensionality reduction and redundance removal processings for the two kind of features, and a fuzzy fusion model for differentiated features is introduced to ensure minimal loss for the feature in fusion. Finally, the structural feature recognition model and grey level feature recognition model are established respectively using the support vector machine, and the final result of the license plate image recognition is achieved in accordance with the high degree of confidence criterion. Simulation results show that the license plate recognition accuracy of the model is up to 99% and recognition time is less than 1.55ms.

2. License Plate Recognition Principles

The license plate recognition principle can be described as: First, the license plate is automatically extracted from an image. Then image feature is extracted. Finally, the license plate is recognized which realizes intelligent vehicle monitoring and management. Known from the license plate recognition principle, license plate character plays vital role in recognition accuracy. Structural characteristics and the image gray feature of the traditional separate image can only describe fragment information in a license plate which cannot fully reflect the license plate category [9]. Multi-feature combination license plate recognition system is a good solution to the defect of traditional identification, mainly include four parts: Structural feature extraction, the gray-scale feature extraction, PCA dimensionality reduction treatment, support vector machine multi-classification. The process is shown in Figure 1

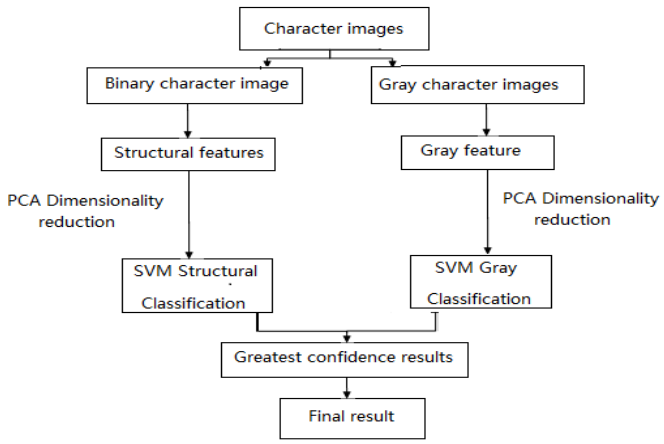

Figure 1. License Plate Recognition Flow Chart with Multi-feature Combination

Multi-feature combination license plate recognition model first extracts the binary structural characteristics and grayscale characteristics of the license plate, reduces the dimension of the extract feature to eliminate duplicate information between features through Principal Component Analysis (PCA), and selects the feature most helpful to improve the license plate recognition accuracy. Then license plate structural features classification model and license plate gray feature classification model are established separately by Support Vector Machine (SVM) with nonlinear and intelligent capabilities. Finally, the discrimination result corresponding to higher degree of confidence from the two models is selected as a license plate final recognition result. The model takes advantage of high performance and simplicity of the structural features, the advantage of, at the same time makes up the losing information defects caused by the binary conversion for the structural characteristics by using of grayscale characteristics, effectively reduces the feature dimension after PCA processing and has high precision, less time-consuming advantages.

3. License Plate Recognition Model with Multi-feature Combination
3.1. License Plate Structural Features Extraction
(1) License plate image binarization

The license plate structural features include outline features and stroke features with the advantages of simple extraction and excellent recognition performance which are normally extracted from the binarization image of the plate characters. For usual plate images, they are binarized first in which they are transferred to the grey model with black/white two colors. By histogram transform method, the images can be transferred to binarization images fast and with high quality. The transferred binarization image is shown in Figure 2.

Figure 2. Binarized License Plate Image

(2) Outline features extraction

The outline feature of the binarization images can well describe the character frame information which has two types-internal and external outline features. The internal outline features (INL) define the amounts of internal black pixels, namely amounts of pixels from the first white-black joint point to black-white joint point; the external outline features (OUL) define amounts of pixels from the image outside to the first white pixel. When compute the outline features of the binarized image, first the character image is divided into nH sub-images from row direction. nH internal outline features and nH external outline features can be obtained from left and right sides which are totally 4*nH outline features. Then, the whole binarized image can be segmented to nK sub-images from row direction. Similarly, nK internal outline features and nK external outline features can be obtained from up and down directions which are 4*nH outline features. Totally 4*(nH+ nK) outline features of the whole image can be obtained.

3.2. License Plate Principle Image Features Extraction
PCA is a kind of high efficient statistical analysis method for feature dimensions reduction in which an optimal feature subset including small amount of unrelated synthesized factors is used to replace the initial multiple feature factors. It can preserve the initial feature information to the maximum extend in order to simplify the initial feature set and remove the redundant information among initial features [10, 11]. For the data set with N samples, and features of $\vec{x}$ (i=1, 2, …., N), the principal component selection procedure is as follows.

First, the mean value m of each feature in the data set is obtained [12-14].

$$\vec{m} = \frac{1}{N}\sum_{i=1}^{N}\vec{x}_i \tag{1}$$

After the mean of each feature sample is obtained, the covariance matrix of the data set is generated.

$$R = \frac{1}{N}\sum_{i=1}^{N}(\vec{x}_i - \vec{m})^T \tag{2}$$

Then, the Jacobi method is used to solve P feature values $\lambda_1 > \lambda_2 > \ldots > \lambda_p$ (after sorting process) which are larger than 0 for the feature function $|R - \lambda I| = 0$. The corresponding feature vectors for each feature value λ_j are as follows.

$$C^{(j)} = (C_1^{(j)}, C_2^{(j)}, \ldots, C_p^{(j)},), (j = 1, 2, \ldots, p) \tag{3}$$

Each feature vectors satisfy the following conditions.

$$C^{(j)}C^{(k)} = \sum_{q=1}^{p} C_q^{(j)} C_q^{(k)} = \begin{cases} 1 & (j = k) \\ 0 & (j \neq k) \end{cases} \tag{4}$$

The initial features are mapped to p principle components Z1, Z2, …, Zp. If the ratio $a = (\sum_{j=1}^{m} \lambda_j) / (\sum_{j=1}^{p} \lambda_j)$ of the covariance sum of the previous m principle components is larger, namely the previous m principle components are preserved principle components, are selected for further analysis. If a larger than 0.85, basically the previous m principle components preserve initial feature information. Thus, 0.85 can be used as threshold to determine the value of m.

3.3. Feature Dimensionality Reduction

Due to that Δ must be obtained first in the identification process, and that Δ is a three-dimensional vector which is comprised of $\Delta x, \Delta y, \Delta z$. Therefore, in order to simplify the calculation, the dimensionality reduction operation is in need for multidimensional vectors. The dimensionality reduction method based on principal component analysis is adopted in this paper, so as to reduce the dimension of the feature space.

The principal component analysis method is a linear dimensionality reduction method, which can obtain the minimum mean square error. The method project the original feature vector into smaller sub-space, so as to reduce the dimension of the original feature vector.

Assuming that the n-dimensional random vector can be expressed as $x = (x_1, \ldots\ldots x_n)^T$, $\bar{x} = E[x]$, the correlation matrix be $R_x = E[xx^T]$, and the covariance matrix can be represented by $C_x = E[(x - \bar{x})(x - \bar{x})^T]$. The dimensionality reduction process can be represented the process that transforming x into $y = (y_1, \ldots\ldots y_n)^T$ by the orthogonal transform. It is calculated as follows:

$$y = U^T x = (u_1, u_2, \ldots. u_n)^T x = \begin{pmatrix} u_1^T \\ u_2^T \\ . \\ . \\ u_n^T \end{pmatrix} x \tag{5}$$

Here, $y_i = u_i^T x$, $i = 1, 2 \ldots. n$.

x can be expressed using the following formula:

$$x = (U^T)^{-1} y = U_y y = U^T x = (U^T)^{-1} y = U_y = (u_1, u_2, \ldots.. u_n) \begin{pmatrix} y_1 \\ y_2 \\ . \\ . \\ y_n \end{pmatrix} = \sum_{i=1}^{n} y_i u_i \tag{6}$$

If just a subset $\{y_1,....y_n\}$ of vector y is reserved for the estimate of x, and the remaining components are replaced using b_i, the formula for the estimate is as follows:

$$\hat{x} = \sum_{i=1}^{m} y_i u_i + \sum_{i=m+1}^{n} b_i u_i \tag{7}$$

The error is:

$$\varepsilon^2(m) = E[(x-\hat{x})^T (x-\hat{x})] = \sum_{i=m+1}^{n} E[(y_i - b_i)^2] \tag{8}$$

By a knowledge of differential calculus, it is obtained that the error is minimum when $b_i = E[y_i] = u_i^T E[x] = u_i^T \bar{x}$. Then:

$$\varepsilon^2(m) = \sum_{i=m+1}^{n} E[(y_i - b_i)^2] = \sum_{i=m+1}^{n} u_i^T C_x u_i \tag{9}$$

In order to make the value of $\varepsilon^2(m)$ be minimum, the differential calculus method is used and by:

$$\frac{\partial J}{\partial u_i} = 0$$

Here, $J = \sum_{i=m+1}^{n} [u_i^T C_x u_i - \lambda_i (u_i^T u_i - 1)]$.

It can be derived that:

$$C_x u_i = \lambda_i u_i, i = m+1,....n \tag{10}$$

Wherein, represents the eigenvalues of the covariance matrix of x, u_i denotes the corresponding eigenvector.

Then,

$$\begin{cases} \varepsilon^2(m) = \sum_{i=m+1}^{n} \lambda_i \\ E[(y_i - \bar{y}_i)^2] = \lambda_i \\ C_y = E[(y_i - y)(y_i - y)^T] = U^T C_X U = \begin{bmatrix} \lambda_1 & & \\ & \lambda_{2....} & \\ & & \lambda_n \end{bmatrix} \end{cases} \tag{11}$$

Thus, by the principal component analysis dimensionality reduction method, the eigenvalue component can be preserved completely, not only simplifying computation, but also save a lot of original information as much as possible.

3.4. Create License Plate Recognition

Multi-recognition data fusion and decision algorithm is used in sonar signal processing to detect the submarine target as early as the 1970s. After years of development, a variety of intelligent data fusion structures, such as fuzzy logic theory, neural networks, DS inference algorithm and so forth, have been created.

The data fusion and decision algorithm proposed in this paper is based on the fuzzy logic theory, and the system block diagram is as follows:

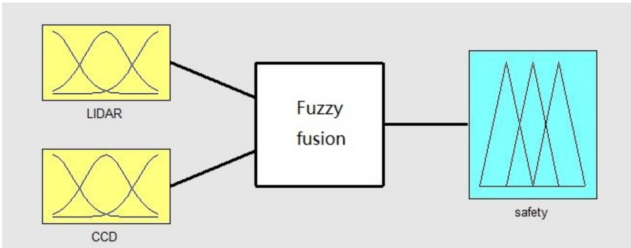

Figure 3. Multi-sensor Image Fuzzy Fusion and Decision Schematic

The fuzzy logic and decision method is adopted to integrate the passive imaging and the captured license plate data, so as to determine the safety of the surface of the license plate. Based on fuzzy logic, the data fusion technology can effectively reflect the expert opinion in the design of membership function. The algorithm is easy to implement and similar to the human way of thinking. The uncertainties in the data is processed by pre-setting the membership function of fuzzy sets.

The fuzzy fusion and decision process of the multi-feature data is divided into three steps: First, the fuzzy processing of the data is carried out in accordance with pre-defined fuzzy set and its membership function. Then, the obtained topographical feature data is used to achieve the reasoning results of the terrain security through the use of fuzzy propositions set described by the language. The fuzzy inference rules used in this paper are shown in Table 1. Finally, the numerical assessed value of the license plate identifiability is obtained through the defuzzification steps (The set of safety assessment values is $[0,1]$).

Table 1. The Fuzzy Inference Rules

Texture	Slope of the license plate			
	Very steep	Steep	Flat	Very flat
Very rough	Poor	Poor	Low	Low
Rough	Poor	Low	Low	Low
Smooth	Low	Low	Medium	High
Very smooth	Low	Low	High	High

As shown in Table 1, the fuzzy set to represent the passive image roughness is defined to contain four elements, that is, {very rough, rough, smooth, very smooth}. And fuzzy set to represent the slope data of the license plate obtained from the imaging equipment is also defined to contain four elements, namely {very steep, steep, flat, very flat}. The fuzzy set to represent the security data consists of four elements, namely {poor, low, medium, high}. The trapezoidal membership function (Figure 4) determined empirically can be set in accordance with the expert opinions. In addition, the membership function is set reasonably, so so to meet the recognition requirements of the area, where the security is "low". Thus, the assessment results of the license plate recognition can be used to provide support for the relevant departments.

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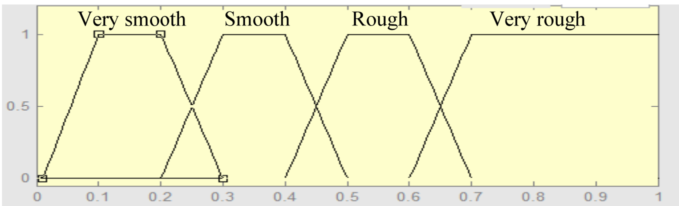

Figure 4. Roughness Membership Function Based on the Image Data

The generated fuzzy logic discriminant surface in accordance with the inference rules in Table 1 is shown in Figure 5:

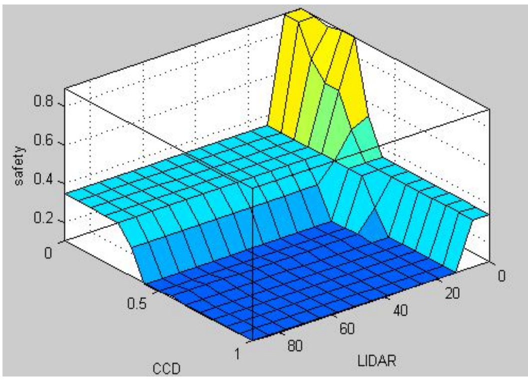

Figure 5. The Fuzzy Logic Discrimination Surface of the Security

3.5. License Plate Recognition

According to the PCA dimensionality reduction method above, the collected feature vector space of the license plate can be processed with dimensionality reduction operation. The Error vector Δ is a multi-dimensional vector, and is broken down into two separate sub-space by PCA dimensionality reduction method: the feature subspace and the non-feature subspace. They are expressed by R and $\overset{\frown}{R}$ respectively. The similarity of the M low-latitude eigen vectors in feature subspace R is:

$$\hat{P}(\Delta|\Omega)=\left[\frac{\exp\left(-\frac{1}{2}\sum_{i=1}^{M}\frac{y_i^2}{\lambda_i}\right)}{(2\pi)^{M/2}\prod_{i=1}^{M}\lambda_i^{1/2}}\right]\bullet\left[\frac{\exp(-\frac{\varepsilon^2(\Delta)}{2\rho})}{(2\pi\rho)^{\frac{(N-M)}{2}}}\right]-P_F(\Delta|\Omega)\bullet P_F(\hat{\Delta}|\Omega) \tag{12}$$

Wherein, $P_F(\Delta|\Omega)$ is the real edge density of subspace R; $\overset{\frown}{R}$ is the edge estimated density; y_i is the main component; $\varepsilon^2(\Delta)$ is the residual energy; The weight parameter ρ can be expressed by the mean value of the characteristic values of the sub-space $\overset{\frown}{R}$ as follows:

$$\rho=\frac{1}{N-M}\sum_{i=M+1}^{N}\lambda_i \tag{13}$$

Here, both $P(\Delta|\Omega_i)$ and $P(\Delta|\Omega_E)$ subject to the two-dimensional Gaussian distribution, and meet:

$$\begin{cases} P(\Delta|\Omega_E) = \dfrac{e^{-1/2}\Delta^r \sum E^{-1}\Delta}{(2\pi)^{\frac{D}{2}}\left|\sum E\right|^{1/2}} \\ P(\Delta|\Omega_i) = \dfrac{e^{-1/2}\Delta^r \sum EI^{-1}\Delta}{(2\pi)^{\frac{D}{2}}\left|\sum I\right|^{1/2}} \end{cases} \tag{14}$$

Wherein, $\sum$ is the covariance matrix.

The steps to calculate the matching similarity of some tested two-dimensional license plate feature sample I_k to a particular two-dimensional license plates library sample I_j are as follows: First, use I_k to subtract I_j, take the result as vector Δ, and then map it to the formula (14). Then, calculate the $P(\Delta|\Omega_i)$ and $P(\Delta|\Omega_E)$ based on the eigen vectors of the primary component of the intra-class and inter-class Gaussian density function. Finally, calculate the degree of matching according to formula (12). In order to simplify the calculation, two albino vectors are added to each image of the library:

$$i_j = \wedge_I^{-1/2} \vee_I I_j \text{ , } i_j = \wedge_I^{-1/2} \vee_I I_j \tag{15}$$

Here, $\wedge$ and $\vee$ are the maximum eigenvalue diagonal matrix and eigenvector matrix corresponding with these eigenvalues of $\sum I$ and $\sum E$ respectively, and the dimensionality of the corresponding sub-spaces are M_I and M_E respectively.

Simplify the probability calculations mentioned above to the simple calculation of euclidean distance:

$$\begin{cases} P(\Delta|\Omega_I) = \dfrac{e^{-1/2}\Delta^T \sum I^{-1}\Delta}{(2\pi)^{D/2}\left|\sum I\right|^{1/2}} \\ P(\Delta|\Omega_E) = \dfrac{e^{-1/2}\Delta^T \sum E^{-1}\Delta}{(2\pi)^{D/2}\left|\sum E\right|^{1/2}} \end{cases} \tag{16}$$

Based at the approximate match in this architecture, there is a more simple form, since only an albino vector i_j for each image is stored. After the completion of the calculation for albino vector i_k of the test samples, the similarity of the degree of association can be calculated using the following formula:

$$S^{'} = P(\Delta|\Omega_I) = \frac{e^{-1/2}\left\|i_j - i_k\right\|^2}{(2\pi)^{D/2}\left|\sum_I\right|^{1/2}} \tag{17}$$

Based on the above analysis, it can be seen that the simple calculation based on two-dimensional license plate similarity is transformed into the calculation of european geometric distance, and the distance can be seen as the degree of association of the multi-feature changes caused by external changes and the recognition. If the score is above 1/2, then the degree of association of this change is higher and the recognition result displays the right license plate, otherwise, it is not the license plate. Thus, the proposed simplified similarity calculation method added with the association degree is more simple and effective.

4. Simulation Experiment

4.1. Experiment Data

In order to simulate the license plate images in complicated environment, all of the license plate images in the experiment are taken in different climate, such as rainy, sunny, cloudy, windy and at night which include different types of plates, such as large freight cars, buses, compact cars and motors. After the license plates are obtained, first the plates are pre-processed. The characters in the plates are isolated to remove the Chinese characters. Then each character is stored in three different formats-initial character image, binarized character image and grey character image to build the character database in the experiment. The character library contains 10945 character images in which 50 characters of each type of character image are randomly selected as test sample.

4.2. Comparison Models

In order to verify the performance of the license plate recognition model with multi-feature combination, the experiment establishes 5 comparison models-single structural feature model (model 1), single grey feature model (model 2); initial feature without PCA dimension reduction (model 3), single model based on structural features and grey features and the dimensions of the initial features are reduced by PCA (model 4), and the parallel model based on structural features and grey features without initial features PCA process (model 5).

4.3. Results and Analysis

The digits and alphabets recognition results of the license plate in each model are shown in table 2. During the recognition training procedure, the digit “0” and alphabet “O” are regarded as “0” and the digit “1” and alphabet “I” are regarded as “1”.

Table 2. License Plate Image Recognition Precisions of each Model

	Digits		Alphabets	
	Precision(%)	Time(ms/piece)	Precision(%)	Time(ms/piece)
Model 1	94.71	1.58	95.64	1.48
Model 2	95.43	0.94	96.35	0.91
Model 3	91.25	1.95	88.68	1.92
Model 4	92.53	1.26	90.19	1.21
Model 5	96.36	2.59	97.71	2.47
Proposed Model	99.37	1.47	99.35	1.32

From the above results, recognition precisions of the proposed license plate model with multi-feature combination are highest among all of the models and they are above 99%. There are following conclusions.

(1) Compared the grey feature model and structural feature model, the recognition precisions of the structural feature model are higher than those of grey feature model. Because the feature dimension is much simpler, the consumed time of the structural feature model is less than that of grey model. It’s obvious that the structural features are better than grey features for simple characters recognition.

(2) Each model is compared with the same model after dimension reduction with PCA. The recognition precisions can be slightly increased after PCA process and the consumed recognition time can be greatly reduced. Especially for the single character in the recognition model with multi-feature combination, the time cost can be reduced by 1ms. Obviously, the feature dimensions can be greatly reduced with recognition time reduced by ensuring recognition precisions.

(3) The simple parallel model utilizes the advantages of grey features and structural features. The recognition precisions are obviously higher than those of single feature model, but the feature dimensions are highest. In all of the comparison models, the consumed time is longest.

(4) The multi-feature combination recognition model can effectively increase license plate recognition precisions by parallel modeling of structural features and grey features. The recognition precisions for digits and alphabets are more than 99%. PCA is used to reduce the dimensions and the time consumption is effectively reduced in which each digit only needs 1.47ms and each alphabet only needs 1.32ms. The recognition precisions of all characters are shown in figure 6. Except “D/0”, “H”, “U” and “M”, the recognition precisions of other characters can reach up to 100%.

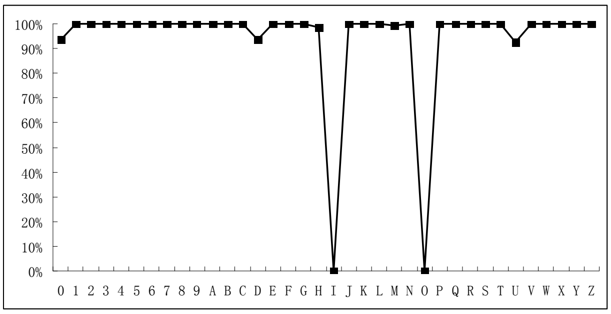

Figure 6. License Plate Characters Recognition Precisions with Multi-feature Combination

5. Conclusion

In order to solve the problems in the license plate recognition, this paper proposes a license plate recognition model with multi-feature combination. This model utilizes the advantages of the structural feature of simplicity and high efficiency to not only increase the recognition precisions of the system, but also save recognition time. Meanwhile, the paper establishes parallel grey feature model which solves the defects of easily losing image information for the structural features. Moreover, PCA is used to reduce the dimensions of the grey features and remove redundancy. Therefore, the multi-feature combination recognition model can not only increase the recognition precision to large extend, but also ensure less time consumption.

References

[1] John Wright, Allen Yang, Arvind Ganesh, Shankar Sastry, Yi Ma. *Robust Face Recognitionvia Sparse Representation.* PAMI. Napa. 2008: 256-263.
[2] D Donoho. Compressed sensing. *IEEE Trans. on Information Theory*. 2006; 52(4): 1289–1306.
[3] RG Baranniuk. Compressive sensing. *IEEE Signal Processing Magazine*. 2007; 24(4): 118–121.
[4] Dalal N, Triggs B. *Histograms of oriented gradients for human detection Proceedings of CVPR’05*. IEEE Computer Society. SanDiego. 2010:886－993.
[5] Shan Jialing. License Plate Recognition System Based on Wireless Network Recognition Algorithm. *Computer Measurement & Control*. 2011; 19(1): 124-126.
[6] Mikolajczyk K, Schmid C. A performance evaluation of local descriptors. *IEEE Transactions on Pattern Analysis & Machine Intelligence*. 2005; 27(10): 1615－1630.
[7] E Cand`es, J Romberg, T Tao Robust. uncertainty principles: Exact signal reconstructionfrom highly incomplete frequency information. *IEEE Trans. on Information Theory*. 2006; 52(2): 489–509.
[8] Wei Gao, Haizhou Ai, Shihong Lao. *Adaptive Contour Features in Oriented Granular Space for Human Detection and Segmentation*. CVPR. San Francisco. 2011:255-363.
[9] Dong Yan, Zhu Yongsheng, Liu Cong. Application of Image Fusion Technology in License Plate Recognition. *Computer Measurement & Control*. 2013; 21(3): 791-793.
[10] Baryon J, Fleet D. Beauchemin S. Performance of optical flow techniques. *Iternational Journal of Computer Vision*. 1994; 12(1): 163-178.

[11] Loumos V, Kayafas E. A License Plate Recognition Algorithm for Intelligent Transp-ortation System Applications. *IEEE Intelli-gent Transportation Systems Society.* 2006; 7(11): 9041-9050.
[12] Gang Li, Ruili Zeng, Ling Lin. Research on Vehicle License Plate Location Based on Neural Networks. *ICICIC*. 2006; 24(8): 174-177.
[13] Cai Yongzhi. License Plate Recognition Based on Improved Neural Network Algorithm. *Bulletin of Science and Technology*. 2012; 28(10): 128-130.
[14] Zhiyi Ruan, Ying Zou, Dongming Hong, Lurong Wu. Visualization of License Plate Recognition System. *International Journal of Electrical and Computer Engineering*. 2013; 11(1): 6714-6721.