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Research Article

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A Self-feedback License Plate Recognition Method Based on Particle Swarm Optimization

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Abstract In the self-feedback template recognition, computational quantity of correlation degree will increase with the increases templates in the template library. A self-feedback license plate recognition method based on particle swarm optimization is proposed to solve the problem of large computational quantity of correlation degree in automatic license plate recognition of the ITS. The effect of the self-feedback license plate recognition method based on particle swarm optimization is analyzed and verified on the platform of MATLAB. Test results show that, under the same accuracy, the correlation degree calculation times and the recognition time of the self-feedback license plate recognition method based on particle swarm optimization are 36.29% and 52.61% of the correlation degree calculation times and the recognition time of the self-feedback template recognition. The performance of self-feedback license plate recognition method based on particle swarm optimization shows that it has high recognition accuracy and recognition speed, and it is suitable for automatic recognition of license plate in the ITS.

Keywords License plate recognition; Particle swarm optimization; Self-feedback; ITS

Introduction

With the expansion and improvement of China's transportation system and the pressure of consuming a lot of human and financial resources in the transportation management system, people use scientific and technological means to assist the traffic control department to realize the real-time monitoring and management of Intelligent Transport System (ITS). As one of the key technologies of ITS, license plate recognition has broad application prospects [1-2].

One of the most effective methods for license plate image recognition is an image recognition method based on template matching. Researchers have proposed many efficient template matching algorithms [3-5]. The number of templates in the template library determines the accuracy of the recognition method to a certain extent, and the greater the number of templates, the lower the efficiency of the conventional recognition method based on traversal means, which ultimately affects the real-time nature of license plate recognition. Aiming at the above-mentioned problems of image recognition based on traversal means, this paper proposes a self-feedback recognition method of license plate based on particle swarm optimization for automatic license plate recognition in intelligent transportation system, combining particle swarm optimization algorithm and self-feedback template recognition method.

Self-feedback template recognition method

Basic algorithm of template matching

Template matching refers to performing a correlation operation on the template image and the image to be matched and obtaining the correlation value, and judging the matching degree of the two based on the correlation value to determine whether there is an area in the image to be matched that is the same as or similar

to the template image, and then complete the target area Location and extraction [6-7]. This method is widely used in the field of image processing [8-9], and its core algorithm is as follows [10]:
Assume that the image to be matched is represented by the function $f(x,y)$, the standard template is represented by the function $F(x,y)$, and the output is $T(x,y)$ after comparison by the correlator. The random variable is represented by the correlation quantity x, y, and the correlator output is:

$$T(x_1-x_2, y_1-y_2)=\iint f(x,y)F\left[x+(x_1-x_2), y+(y_1-y_2)\right]dxdy \quad (1)$$

When $x_1=x_2, y_1=y_2$,

$$T(0,0)=\iint f(x,y)F(x,y)dxdy \quad (2)$$

When $f(x,y)=F(x,y)$,

$$T(0,0)=\iint f(x,y)f(x,y)dxdy \quad (3)$$

The above is the autocorrelation function of the image to be matched, and $T(0,0)\geq T(x,y)$. $T(x,y)$ has a main peak at $T(0,0)$ and secondary peaks in other areas. You can use an appropriate threshold to identify the main peak to identify and locate the target image area.

PSO-based self-feedback recognition method

Principle of self-feedback identification method

Although shape-based matching is the most basic and practical template matching method [11]. However, the basis of the template matching algorithm is template extraction. Its essence is to determine the key shape features through the template to determine whether there is a target image in the image to be matched. Therefore, the number of target image recognition features contained in the established template library becomes the key to judge the template extraction method and the image recognition effect [12-13]. Some researchers have proposed a self-feedback template extraction method that uses the results of the previous recognition as the later recognition template. This method makes full use of the early recognition results, fills the template library through the recognition process, and then realizes the adaptation of the template library, improves the utilization rate of the early recognition results and the accuracy of the later stage, and finally achieves the purpose of optimal resource utilization and recognition effect. The principle is as follows [3].
Let the number of all necessary features of the target image is E; the number of features of the initial template is E_0; the number of features not included in the initial template is $E^{'}$, then $E^{'}=E-E_0$.
Let the number of features included in the n recognition result is R_n, the corresponding template generated is M_n, the correlation threshold used to identify the target image is s, and use $E_n^{'}$ to indicate that each recognition result contains more than the number of necessary features last time, use $E(\sum_{i=0}^{n-1}M_i)$ represents the number of non-repetitive features of all the templates used for the first recognition, which can be obtained:

$$\begin{cases} R_1=E(\sum_{i=0}^{0}M_i)\times s=E_0\times s+E_1^{'}=M_1 \\ R_2=E(\sum_{i=0}^{1}M_i)\times s=E(M_0\cup M_1)\times s=(E_0+E_1^{'})\times s+E_2^{'}=M_2 \\ R_3=E(\sum_{i=0}^{2}M_i)\times s=E(M_0\cup M_1\cup M_2)\times s=(E_0+E_1^{'}+E_2^{'})\times s+E_3^{'}=M_3 \\ \vdots \\ R_n=E(\sum_{i=0}^{n-1}M_i)\times s=E(M_0\cup M_1\cup M_2\cup\cdots\cup M_{n-1})\times s=(E_0+E_1^{'}+E_2^{'}+\cdots+E_{n-1}^{'})\times s+E_n^{'}=M_n \end{cases} \quad (4)$$

Let $n\to\infty$ get n identifications and extract the number of non-repeating features contained in the template library after:

$$\lim_{n\to\infty} E(\sum_{i=0}^{n} M_i) = E(M_0 \cup M_1 \cup M_2 \cup \cdots \cup M_n)$$
$$= E_0 + E_1^{'} + E_2^{'} + \cdots + E_n^{'} = E_0 + E^{'}$$
$$= E_0 + E - E_0 = E \qquad (5)$$

Principle of particle swarm optimization algorithm

The particle swarm optimization algorithm [14-15] (PSO) is based on the observation of the behavior of animal clusters, using the information shared by the individuals in the group to make the movement of the entire group from disorder to order in the problem solving space. The evolutionary process of the process to obtain the optimal solution. In the particle swarm optimization algorithm, the potential solution of each optimization problem is called "particle". All particles are a fitness value determined by the optimized function, and each particle has a speed that determines the direction and distance they fly. Then the particles follow the current optimal particle and search in the solution space. The particle swarm optimization algorithm is initialized as a group of random particles (random solutions). Then iterate to find the optimal solution. In each iteration, the particle updates itself by tracking two "extreme values": the first is the optimal solution found by the particle itself, and this solution is called the individual best point; the best solution currently found by the entire population. This solution is the global best. In addition, instead of using the entire population, only a part of them can be used as the neighbors of the particles, then the extreme values in all neighbors are local extreme values. Particle swarm optimization algorithm is an intelligent algorithm realized by constantly updating extreme points.

Suppose that in an N -dimensional target search space, there are M particles representing potential solutions to form a population, where the position of particle i in N -dimensional space is represented by vector $X_i = (x_1, x_2, \cdots, x_N)$ and the flight speed is represented by vector $V_i = (v_1, v_2, \cdots, v_N)$.

For the t -th iteration, each particle in the PSO changes according to the following formula:

$$V(t+1) = wV(t) + c_1 rand(p_{best}(t) - X(t)) + c_2 rand(g_{best} - X(t)) \qquad (6)$$

$$X(t+1) = X(t) + V(t+1) \qquad (7)$$

Where V is the velocity of the particle, w is the inertial weight, and c_1 and c_2 are learning factors, that is the maximum step size for the global best particle and the individual best particle is adjusted separately. If it is too small, the particles may be far from the target area if it is too large, it will suddenly fly to or over the target area. Usually let $c_1 = c_2 = 2$. rand is a random number between [0,1], X is the current position of the particle, p_{best} is the current best position of the particle, which isthe local optimal, and g_{best} is the current best position of the population, which is the global optimal.

The particle swarm optimization algorithm has the following advantages:

1) There is no centralized control constraint, and it will not affect the solution of the entire problem due to the failure of individual individuals, ensuring that the system is more robust;

2) Parallel operations can be performed on the search space, and the search process of each individual can also be performed in parallel. The advantage of parallel computing can greatly reduce the time to solve the problem when solving optimization problems with a very large amount of computational complexity. ;

3) There is no special requirement for the continuity of the problem definition. This is a very good property of the particle swarm algorithm that is different from the traditional optimization algorithm, and its application range can be expanded.

Self-feedback recognition method of license plate based on PSO

Although the self-feedback template recognition method can improve the recognition accuracy, it has certain disadvantages, that is, as the number of templates in the template library increases, the number of template correlation calculations increases, reducing the efficiency of the recognition method. According to the principle of PSO, the search process of PSO particles can be carried out in parallel, which can greatly reduce the time to solve the problem when solving the optimization problem with huge calculation amount and complex scale. This feature of PSO can solve the problem of a large increase in the amount of calculation in the self-feedback template recognition method as the number of templates in the template library increases.

Therefore, this paper proposes a PSO-based self-feedback recognition method for license plates, using PSO to select the template in the template library that is most relevant to the image to be matched to determine the license plate number in the image to be matched. The method flow is as follows:

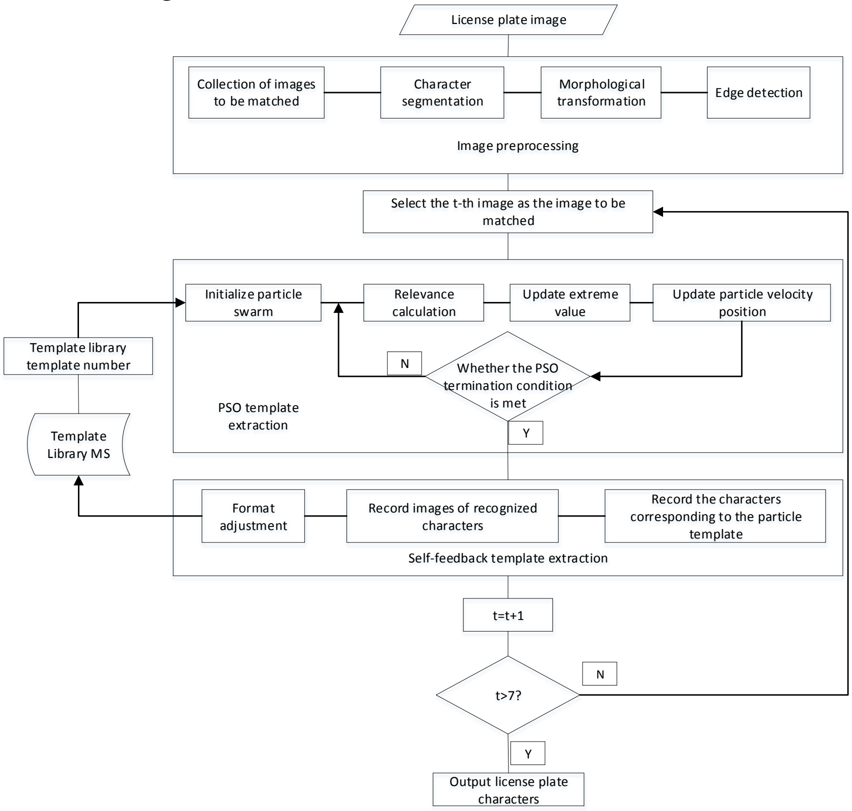

Figure 1: PSO-based license plate self-feedback recognition method flow chart

(1) Image initial processing

The image P_0 containing the license plate is subjected to edge detection, morphological transformation and character segmentation to generate a set $A=\{A_1, A_2, \cdots, A_7\}$ of images to be matched.

(2) Image recognition based on template matching

For the existing template number, initialize the PSO particle group, use formula (1) to calculate the spatial domain correlation between the existing template particle image (denoted by $F_j(x,y), j=1,2,\cdots,n_s$, n_s is the total number of particle template images) and the image to be matched (denoted by $f_i(x,y)$), Take the maximum correlation as the PSO optimization goal, update the extreme value, particle speed, and particle position, and determine whether the termination condition is met (the maximum number of iterations is reached or the optimization accuracy is reached).

(3) Extraction of self-feedback template

The characters corresponding to the particle template are recorded, and the recognized character image is adjusted to the template file format and stored in the template library *MS* .

(4) Iteration of the process

Perform image recognition until the 7 characters of the license plate are recognized.

(5) Results output

The recognized license plate characters are output.

Example verification and effect analysis

On the basis of MATLAB software, make full use of the software's rich operators and integrated functions to implement the PSO-based license plate self-feedback recognition method described in this paper. First, the recognition of a single character image of a license plate as an example to explain the process in detail, and then the processing data of each image analyzes the effectiveness of the method described in this article.

License plate character recognition

(1) Image initial processing

Use the Canny operator with separation filtering and Gaussian smoothing to perform edge detection, and then perform appropriate morphological processing to divide characters by calculating the cumulative value of non-zero gray pixels in the row and column directions to complete the initial processing of the image.

Figure 2: Original image, edge detection effect, dilation effect

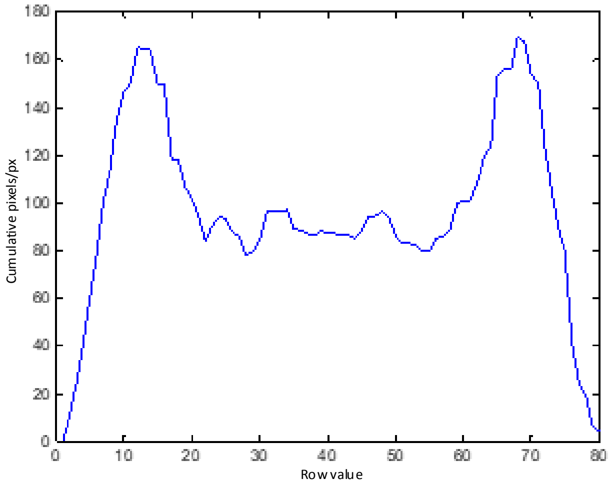

Figure 3: Row direction grayscale cumulative map

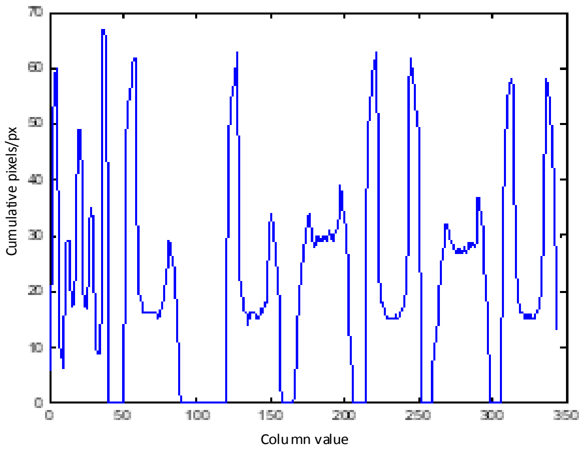

Figure 4: Column direction grayscale cumulative map

Figure 5: Image after character segmentation

(2) Image recognition based on template matching

For the existing template number, initialize the PSO particle group, set the learning factor $c_1 = c_2 = 2$, inertia weight $w = 0.7$, set the PSO iteration termination condition to reach 80% correlation, use equation (1) to calculate the spatial correlation between the existing template particle image and the i-th image, the maximum correlation is used as the PSO optimization goal, and the extreme value, particle velocity, and particle position are updated until the PSO iteration termination condition is met.

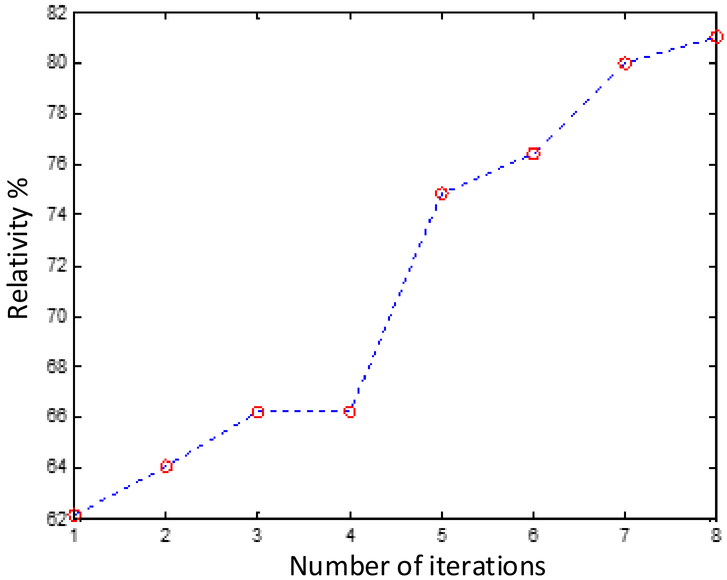

Figure 6: The correlation curve of character "C" solved by PSO

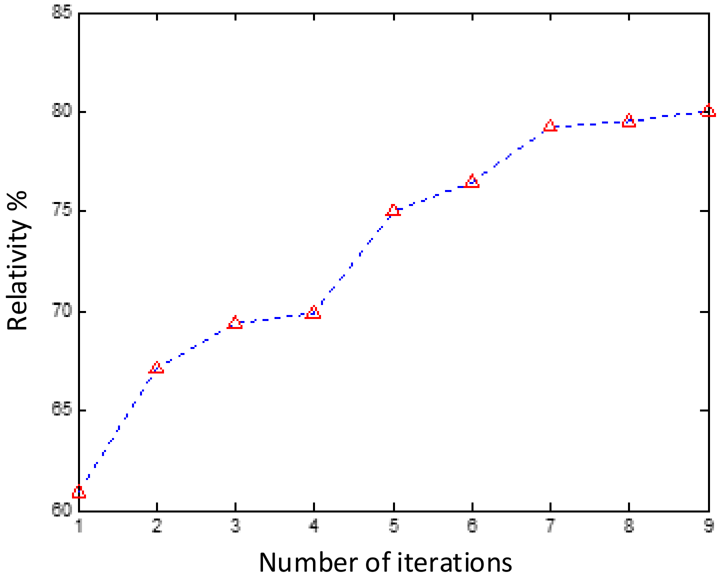

Figure 7: The mean curve of the correlation of the character "C" solved by PSO

Note: Perform 10 PSO solutions, the maximum number of iterations is taken, and the correlation of each iteration is averaged

(3) Extraction of self-feedback template

The characters corresponding to the particle template are recorded, and the recognized character image is adjusted to the template file format and saved in the template library *MS* .

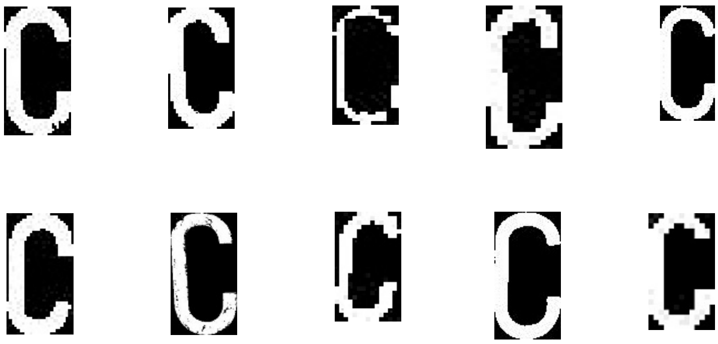

Figure 8: Existing templates

Figure 9: Self-feedback extracted template

(4) Process iteration and result output

Image recognition is performed until 7 characters of the license plate are recognized, and the recognized license plate characters are output.

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Figure 10: License plate recognition effect

Identification effect analysis

Using 10 license plate images as the images to be detected in turn, image recognition based on the original self-feedback template extraction method and image recognition based on the method in this paper are performed. The recognition results based on the self-feedback template extraction method are shown in Table 1, and the recognition results based on the recognition method in this paper are shown in Table 2.

Table 1: Identification results based on self-feedback template extraction method

Group	**Number of goals/Pc**	**Identification number/Pc**	**Accuracy /%**	**Relevance calculation times /frequency**	**Recognition time /ms**
1	7	7	100	1775	3886
2	7	7	100	1774	3703
3	7	7	100	1845	3730
4	7	7	100	1821	3880
5	7	7	100	1797	3601
6	7	7	100	1806	3617
7	7	7	100	1827	4011
8	7	7	100	1808	3828
9	7	7	100	1767	3814
10	7	7	100	1838	3763
Mean	7	7	100	1805.80	3783.30

Table 2: The recognition results based on this method

Group	**Number of goals/Pc**	**Identification number/Pc**	**Accuracy /%**	**Relevance calculation times /frequency**	**Recognition time /ms**
1	7	7	100	677	1679
2	7	7	100	566	1644
3	7	7	100	697	2596
4	7	7	100	716	2801
5	7	7	100	596	2016

6	7	7	100	714	1469
7	7	7	100	669	1528
8	7	7	100	658	2423
9	7	7	100	598	1644
10	7	7	100	663	2105
Mean	7	7	100	655.40	1990.50

Since the PSO termination condition is set to achieve a correlation of 80%, the recognition accuracy of the method described in this paper and the self-feedback template extraction method both reach 100%. However, the self-feedback template extraction method uses the traversal method to calculate the correlation between the template in the template library and the characters to be recognized, resulting in that the recognition method correlation calculation times described in this paper are 36.29% of the self-feedback template extraction method correlation calculation. Because the recognition method described in this article requires particle swarm initialization, particle update, etc., the advantage of recognition time is not as significant as the number of correlation calculations, but the recognition time of the recognition method described in this article is only the calculation time of the self-feedback template extraction method. 52.61%.

Comparing the recognition results, it can be seen that the self-feedback recognition method of license plate based on particle swarm optimization proposed in this paper has higher recognition accuracy and has a faster recognition speed than the self-feedback template extraction method.

Conclusion

This paper analyzes the characteristics of the self-feedback template recognition method, clarifies the need to improve the efficiency of the self-feedback template recognition method using intelligent algorithms, introduces the particle swarm optimization algorithm principle, analyzes the advantages of the particle swarm optimization algorithm, and proposes a particle swarm Optimized license plate self-feedback recognition method. On the MATLAB platform, the basic self-feedback template extraction method and the particle swarm optimization-based self-feedback recognition method were used to recognize the characters of the license plate. The recognition accuracy, the number of correlation calculations, and the recognition time were used as evaluation indicators. The recognition effects are compared, which proves that the self-feedback recognition method of license plate based on particle swarm optimization proposed in this paper has higher recognition accuracy and faster recognition speed.

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