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Fuzzy traffic signal control with DNA evolutionary algorithm

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Abstract: In order to optimize the signal control system, this paper proposes a method to design an optimized fuzzy logic controller (FLC) with the DNA evolutionary algorithm. Inspired by the DNA molecular operation characteristics, the DNA evolutionary algorithm modifies the corresponding genetic operators. Compared with the traditional genetic algorithm (GA), the DNA evolutionary algorithm can overcome weak local search capability and premature convergence. The parameters of membership functions are optimized by adopting the quaternary encoding method and performing corresponding DNA genetic operators. The relevant optimized parameters are combined with the FLC for single intersection traffic signal control. Simulation experiments shows the better performance of the FLC with the DNA evolutionary algorithm optimization. The experimental results demonstrate the efficiency of the proposed method.

Key words: DNA evolutionary algorithm; genetic algorithm (GA); fuzzy control; traffic signal control

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Traffic signal control has attracted considerable interest because road traffic congestion is a critical problem. The fuzzy logic theory has played an important role in adaptive traffic signal control in recent years. Pappis et al. [1] first proposed an implementation of a fuzzy logic controller (FLC) in a single intersection of two one-way streets in 1977. Trabia et al. [2] developed a fuzzy logic controller for an isolated four-approach signalized intersection which mainly determines whether to extend or terminate the current signal phase. Murat and Gedizlioglu[3] developed a fuzzy logic multi-phased signal control model for isolated signalized intersections. In addition, the use of the optimized method has demonstrated its usefulness in traffic signal distribution strategy. Srinivasan[4] presented a real-time traffic signal control method based on neural networks. Anderson et al. [5] proposed a GA-optimized fuzzy logic controller traffic signal control. Garcia-Nieto et al. [6] utilized the particle swarm optimization (PSO) method for traffic light scheduling. Dimitriou et al. [7] presented an adaptive hybrid fuzzy rule-based system (FRBS) approach.

However, the DNA evolutionary algorithm can overcome the drawbacks of the GA, such as weak local search capability and premature convergence[8-9]. In this paper, we propose a fuzzy logic controller for traffic signal control and utilize the GA and the DNA evolutionary algorithm to optimize FLC membership function parameters, respectively. Then the optimized FLC is applied to traffic signal control.

1 Fuzzy Logic Controller for Signal Control

In this paper, we consider a single traffic junction with multiple lanes. The number of street lanes ranges from 1 to 3, as shown in Fig. 1.

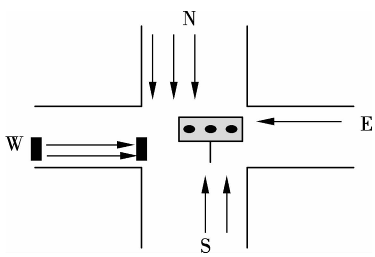

Fig. 1 A single traffic junction with multiple lane

As shown in Fig. 1, each group of traffic loop detectors consists of two sensors, one at the downstream stop line for recording the departure vehicles and the other at the corresponding intersection upstream for estimating the arriving vehicles. For multiple lanes, drivers tend to switch to a shorter queue while approaching the junction, so the differences among queue lengths of all the lanes in the same direction are usually small. If the north-south direction is in the green phase, then we can let

G = max {queue lengths of all lanes in north and south directions}

R = max {queue lengths of all lanes in east and west directions}

At the beginning of every phase, G and R are measured, which are the two input variables of the fuzzy logic

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controller. We select the green time of the current phase T as output variable. Without loss of generality, we adopt the same Gaussian membership function of which the universe of discourse is (0, 12).

All these variables are divided into seven fuzzy language partitions: very short(VS), medium short(MS), short(S), medium(M), long(L), medium long(ML), and very long(VL). The rule base is shown in Tab. 1.

Tab. 1 Fuzzy inference rule base

G	R						
	VS	MS	S	M	L	ML	VL
VS	VS	VS	VS	VS	VS	VS	VS
MS	MS	MS	MS	MS	MS	VS	VS
S	S	S	S	S	S	MS	MS
M	M	M	M	M	M	S	MS
L	L	L	L	M	M	S	MS
ML	ML	ML	ML	L	L	M	S
VL	VL	VL	ML	ML	L	L	M

2 Optimization Process with DNA Evolutionary Algorithm

2.1 DNA evolutionary algorithm and encoding principle

The DNA evolutionary algorithm adopts the characteristics of the DNA model, which encodes chromosomes and amends genetic operators with the DNA nucleotide mechanism. The DNA algorithm has several kinds of operators as follows:

1) Selection operator. Elitism is used with tournament selection in attempt to guarantee the best individual to be replicated into the next generation.

2) Translocation operator. This operator makes the subsequence of the DNA sequence transfer to a new location. For example, let the original DNA sequence be $X = X_5X_4X_3X_2X_1$, where $X_i(i=1,2,\ldots,5)$ is the subsequence of the DNA sequence (X). Then the new sequence after the translocation operation becomes $X = X_5X_2X_4X_3X_1$.

3) Transformation operator. This operator makes the segments of the DNA sequence exchange their locations. For example, the sequence X after a transformation operation which exchanges X_4 with X_2 becomes $X = X_5X_2X_3X_4X_1$.

4) Permutation operator. One subsequence of the DNA sequence is permutated by the other subsequence. For example, when X_2' subsequence from the same or other DNA sequence is selected to replace X_2, the new sequence is $X = X_5X_4X_3X_2'X_1$.

5) Mutation operator. In order to maintain the population diversity, we employ the shifty probability in different evolution stages. At the beginning of the evolution stage, we want to have a large probability in the high bit position so as to obtain a large searching space. At the end of the evolution stage, the large probability in the low bit position is necessary for acquiring more accurate results. So there are two kinds of mutation probability P_{h} and P_{l},

$$P_{\mathrm{h}} = a_1 + \frac{b_1}{1+\exp[a(g-g_0)]} \tag{1}$$

$$P_{\mathrm{l}} = a_1 + \frac{b_1}{1+\exp[-a(g-g_0)]} \tag{2}$$

where a_1, b_1, g, g_0 and a denote the initial mutation probability, the range of the mutation probability, the evolutionary generation, the generation where the great change of mutation probability occurs, and the speed of change, respectively.

2.2 Procedure of DNA genetic algorithm

On the basis of the DNA encoding principle and corresponding genetic operators, for the Gaussian membership function, two input variables and one output variable are encoded in a 42 real gens chromosome by using the quaternary encoding method. The procedure of the DNA genetic algorithm is as follows:

Step 1 Initialize population N and evolutionary generation G_{en} and encode the individuals using the DNA encoding method.

Step 2 Set the fitness function and calculate the individuals' fitness values.

Step 3 Implement the selection operator with elitism from the population so as to select the individuals of high value and reproduce similar individuals.

Step 4 Utilize the permutation operator and set the random number with the range of [0, 1]. If the random number $i > p_{\mathrm{c}} = 0.5$, implement the translocation operator, otherwise implement the transformation operator.

Step 5 Calculate P_{h}, P_{l} and implement the mutator operator. On the basis of the Watson-Crick complementary principle, produce N corresponding complementary individuals after the mutation operation. Then the population is enlarged with $2N$ individuals.

Step 6 If the criterion is met or the loop of the evolutionary process is completed, end this algorithm. Otherwise, repeat from step 2 to step 6 until the final optimized solutions are found.

3 Simulation

3.1 Queue length and average delay model

In order to illustrate the validity of the methods for traffic signal control, the intersection queue lengths and the average delays are usually selected as criteria. In this model, assume that the arrival time of vehicles is random. In each successive time unit (1 s), if a vehicle arrives during the n-th unit interval, let $q_n = 1$. Otherwise, let $q_n = 0$. V_{G} denotes the number of vehicles that cannot leave during the previous green phase. V_{R} denotes the number of vehicles that arrive during the red phase. Then the queue lengths of the red phase and the green phase after the n-th time unit Q_{R}, Q_{G} are depicted as

$$Q_{\mathrm{R}} = \left\lceil \frac{V_{\mathrm{G}} + \sum_{i=1}^{n} q_i}{p} \right\rceil \tag{3}$$

$$Q_{\mathrm{G}} = z\left\{ \left\lceil \frac{V_{\mathrm{R}} + \sum_{i=1}^{n} q_i}{p} \right\rceil - sn \right\} \tag{4}$$

where p is the number of lanes; $z=1$ if $\left\lceil \frac{V_{\mathrm{R}} + \sum_{i=1}^{n} q_i}{p} \right\rceil - sn$ is nonnegative, otherwise $z=0$.

The total delay time of the vehicles at the red phase of this cycle is

$$D_{\mathrm{R}} = \sum_{j=1}^{n} \left(V_{\mathrm{G}} + \sum_{i=1}^{j} q_i \right) \tag{5}$$

Then the total waiting time at the green phase of this cycle can be described as

$$D_{\mathrm{G}} = \sum_{j=1}^{n} z\left(V_{\mathrm{R}} + \sum_{i=1}^{j} q_i - sjp \right) \tag{6}$$

where $z=1$ if $V_{\mathrm{R}} + \sum_{i=1}^{j} q_i - sjp$ is nonnegative, otherwise $z=0$; s denotes the number of vehicles that leave per second.

Therefore, during the l-th cycle the total delay time experienced by vehicles and the average delay time are

$$D^l = D_{\mathrm{R}}^l + D_{\mathrm{G}}^l \tag{7}$$

$$d^l = \frac{D^l}{g^l + r^l + g^{l-1} + r^{l-1}} \tag{8}$$

where g^l and r^l are the numbers of vehicles that arrive at the green phase and the red phase in the l-th cycle, respectively; g^{l-1} and r^{l-1} are the numbers of vehicles that stay at the green phase and the red phase in the previous cycle, respectively.

3.2 Simulation results

In our optimization process, the aim is to minimize the average delay time in the total cycle; i.e., $f = \min \sum_{l=1}^{n} d^l$. The basic domains of $G(R)$ and T are selected as [0, 30] and [5, 55], respectively.

According to the queue length and the average delay model, simulation experiments are constructed by varying the arrival rates of vehicles. Different control methods are compared, which include the fixed-time control, the FLC that does not use any optimization technique, the GA optimized FLC (GA_FLC), and the FLC with DNA optimization (DNA_FLC). Simulation results are shown in Tab. 2 and Fig. 2.

From Tab. 2, we can see that the delay time of FLC with the DNA genetic algorithm optimization is significantly shortened compared with the other methods at different vehicle arrival rates. Especially, when the arrival rate of vehicles is high, the difference of these methods is bigger. Fig. 2 compares the total queue length for different arrival rates of vehicles given by different methods. Especially, from Fig. 2(b) we can see that when the traffic becomes heavy, the method with the DNA optimization can let vehicles evacuate instead of gathering in other methods. It illustrates that the FLC with the DNA genetic algorithm optimization shows more superiority when traffic flow is heavy.

Tab. 2 Results of simulation

Arrival rate of vehicles		Delay time/($\mathrm{s \cdot vehicle^{-1}}$)			
$r_{\text{N-S}}$	$r_{\text{W-E}}$	Fixed cycle	FLC	GA_FLC	DNA_FLC
0.1	0.1	4.699 2	3.466 8	3.258 4	3.075 8
0.1	0.2	6.580 7	5.157 5	4.906 8	4.585 6
0.1	0.3	9.935 3	8.402 3	6.252 8	6.112 1
0.1	0.4	13.873 8	12.636 3	11.438 2	11.195 8
0.2	0.2	6.171 9	4.803 1	4.589 7	4.358 3
0.2	0.3	9.767 3	8.123 4	6.124 4	6.019 4
0.2	0.4	13.825 4	12.298 4	10.876 1	10.410 7
0.3	0.3	9.869 3	8.366 4	6.150 9	5.497 4
0.3	0.4	13.909 0	12.272 3	10.839 5	9.974 5
0.4	0.4	14.255 3	13.047 1	12.162 9	11.086 5

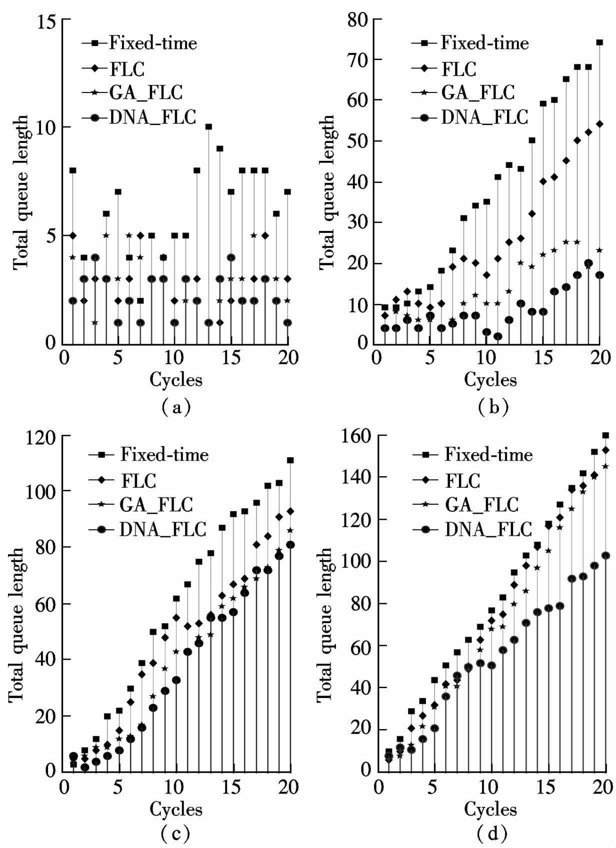

Fig. 2 Queue length in different arrival rates under four methods. (a) $r_{\text{N-S}}=0.2$, $r_{\text{W-E}}=0.2$; (b) $r_{\text{N-S}}=0.3$, $r_{\text{W-E}}=0.3$; (c) $r_{\text{N-S}}=0.3$, $r_{\text{W-E}}=0.4$; (d) $r_{\text{N-S}}=0.4$, $r_{\text{W-E}}=0.4$

4 Conclusion

In this paper, we design a fuzzy logic controller based on the DNA evolutionary algorithm and apply the optimized fuzzy logic controller to simulate single intersection signal control. The DNA evolutionary algorithm inherits the advantages of the GA and adds DNA molecular operation characteristics. It presents better searching capability and maintains diversity of the population. Compared with the fixed-time controller, the traditional fuzzy logic controller and the fuzzy logic controller optimized by the GA, the proposed fuzzy logic controller shows better performance in the distribution of green/red time.

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基于DNA进化算法的模糊交通信号控制

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摘要:为了优化交通信号控制系统,提出了一种基于DNA进化算法的模糊逻辑控制优化方法.受DNA分子运算特征的启发,DNA进化算法修改了相应的遗传算子.与传统的遗传算法相比,它可以克服局部搜索能力小和早熟的弱点.通过采用四进制编码方式和执行相应的DNA遗传算子来优化模糊逻辑控制器隶属度函数的参数,并把优化的参数结果运用到单交叉口交通信号控制.仿真实验结果表明,DNA优化的模糊逻辑控制方法表现更好,从而证明了该方法的有效性.

关键词:DNA进化算法;遗传算法;模糊控制;交通信号控制

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