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Artificial Traffic Light using Fuzzy Rules and Neural Network

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Abstract:

This paper proposes a new concept of optimal shortest path algorithm which reduce average vehicle wating time and improve average vehicle speed. Electro sensitive traffic system can extend the traffic cycle when there are many vehicles on the road or it can reduce the traffic cycle when there are small vehicles on the road. But electro sensitive traffic light system dosen't control that kind of function when the average vehicle speed is 10km - 20km. Therefore, in this paper to reduce vehicle waiting time we developed design of traffic cycle software tool that can arrive destninatiion as soon as possible using optimal shortest pass algorithm . Computer simulation result proved 10% - 32% reducing average vehicle wating time and average vehicle speed which can select shortest route using built in G.P.S. vehicle is better than not being able to select shortest route function .

Keywords: Vehicle waiting time, Passenger car unit, Shortest path route

I . Introduction

Traffic signal cycle optimization is one of the most efficient ways for reducing fuel consumption and improving VEHICLE WAITING TIME from highly saturated traffic conditions [1-3]. Research for a traffic signal control based on fuzzy logic have been conducted to optimize traffic flow [4-7]. In order to overcome these conventional traffic signal, the traffic signal must reduce the average vehicle waiting time and improve average vehicle speed[8-9]. The electro-sensitive traffic control system antecedently recognizes a passenger car unit using neural networks. However mistakes occur due to changes in car weight, speed, and passing area. Consequently, to reduce the car waiting time and start-up delay time we use fuzzy control of feed-back data. If we improve average vehicle speed by just 10-15%, this will save approximately 2 million dollars per year.

With computer simulation, we prove that the spillback phenomenon generated under highly saturated traffic condition is improved using fuzzy logic and neural networks. This paper is organized as follows. Section II briefly explain Estimating vehicle length. Section III discusses the shortest pass algorithm. Section IV describe determination of optimal traffic cycle using neural network and fuzzy logic computer simulation. Finally, Section V give the conclusions.

II. Estimating vehicle length

When upper intersection is highsaturated and consits of vehicles , spillback is generated and traffic congestion occurs at the traffic signal. Therefore, to prevent spillback we must estimate vehicle length and passenger car unit. Moreover, large car left-turn departure time is 1.3 seconds longer than straight departure time and a bus or a truck has a value of 1.5 times of a passenger car. In order to improve vehicle waiting time and spillback phenomenon we must consider vehcile length and passenger car time. Therefore, in this paper we proposed fuzzy neural traffic light that estimate vehicle length using fuzzy rules and improve average vehicle speed and spillback phenomenon.

Table 1. Passing vehicle of expecting P.C.U. and expecting waiting queue length

Saturation rate of upper traffic intersection	Passing vehicle of Lower traffic Intersection	Expecting passenger car unit	Expecting vehicle length	Total vehicle queue length
Saturation Rate	T1 T2 T3 T4 T5	P1 P2 P3 P4 P5	W1 W2 W3 W4 W5	$\sum_{i=1}^{5} W*(i)$
High saturation	1 1 0 1 1	1.3 1.2 1.2 1.5 1.3	6.5 5.6 5.6 8.7 6.3	32.7 M
Low saturation	1 1 0 1 1	1.2 1.4 1.6 1.2 1.3	5.6 6.8 9.6 5.6 6.3	33.9 M
Low saturation	1 1 1 1 1	1.2 1.2 1.9 1.4 1.7	5.6 5.6 14.3 6.8 10.5	42.8 M
Low saturation	1 1 0 0 1	1.6 1.8 1.9 1.2 1.9	9.6 12.8 14.6 5.6 14.8	57.4M

As You can see Table 1, to solve spillback phenomenon we must calculate number of passing vehicles using loop detector and determine which car is big or small.

If approaching vehicle Speed is 20Km/hour, Total weight is 1500Kg, and passing area of loop detector is 80 %, it can be written Eq.(1).

Passenger car unit= Veh(spd),Veh(pwr),Veh(twt) ....(1)

Expecting vehicle length = 12 Meter

If approaching vehicle speed is 5Km, Total weight is 550Kg, and passing area of loop detector is 80 %, it can be written Eq. (2).

Passenger car unit= Veh(1/4spd),Veh(pwr),Veh(1/3twt)..(2)

Expecting vehicle length = 5 Meter

If approaching vehicle speed is 10Km/hr total weight is 550Kg, and passing area of the loop detector is 40 %, it can be written Eq. (3).

Passenger car unit =Veh(1/2spd),Veh(1/2pwr),Veh(1/3twt) ....(3)

Expecting vehicle length = 6.5 Meter

III. Shortest Pass Algorithm

```
void ai_short()

trf[ 1][ 7] = 5; trf[ 2][ 7] = 9; trf[ 3][ 8] =14; trf[4][13] = 10;
trf[5][26] = 2;  trf[ 6][19] = 2; trf[ 7][ 8] = 7; trf[ 8][ 9] = 1;
trf[ 9][10] = 4; trf[ 9][12] =10; trf[ 9][17] = 8; trf[10][11] = 2;
trf[10][16] = 1; trf[11][12] = 1; trf[11][15] = 3; trf[11][17] = 4;
trf[12][13] = 2; trf[12][14] = 2; trf[13][14] = 1; trf[13][21] = 2;
trf[14][15] = 1; trf[14][20] = 2; trf[15][18] = 4; trf[15][20] = 1;
trf[16][17] = 3; trf[16][18] = 3; trf[17][19] = 3; trf[18][19] = 5;
trf[18][24] = 2; trf[19][25] =12; trf[20][21] = 1; trf[20][24] = 3;
trf[21][22] = 1; trf[21][26] = 9; trf[22][23] = 2; trf[22][25] = 3;
trf[23][26] = 8; trf[24][25] = 3;

    /*  A.I. - Short Pass Algorithm */

  printf(" start "); scanf("%d", &start);

    for (k=1;k<=N; k++)
      {
speed[k]=M;    /* Average vehicle speed  */
v[k]=0;               /* Confirm Flag */
      }

speed[start]=0;
index[start]=0;    /* shortest distance */
```

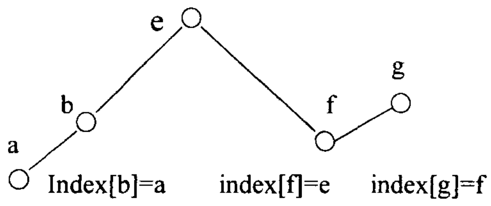

Fig 1. Shortest pass Distance

```
/* shortest pass algorithm */

        for (k=1; k<N; k++)
        {
  if (( speed[p]+a[p][k])<speed[k])
          {
          speed[k]=speed[p]+a[p][k];
          index[k]=p;
          }
```

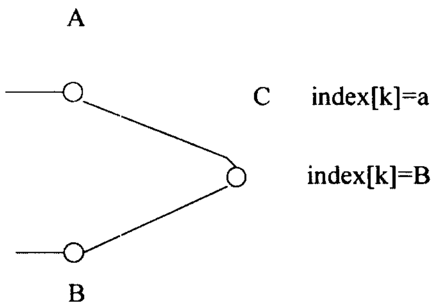

Fig 2. Finding for shortest pass Distance

IV. Calculation of passenger car unit using neural network and fuzzy logic

A learning process which adjusts weights and connection intensity of neural network can be classified into supervised learning process and unsupervised learning process according to the existence or non-existence of supervised signal. We use supervised learning process which adjust weights to reduce the error between desired output and real output. This is depicted as follow.

(1) Initialize Weights and Offset

(2) Establishment of training pattern

(3) Compute the error between target pattern output layer neural cell(tj) and output layer neural cell(aj)

$$e_j = t_j - a_j \quad \text{.......(5)}$$

(4) calculate weights between input neural cell(i,j) by follow equation

$$W(new)_{ij} = W(old)_{ij} + \alpha e_{iaj} \quad \text{.......(6)}$$

$$e_j = t_j - a_j \quad \text{.......(7)}$$

(5) Repeat the progress from number (2) above. process is repeated until all weights reach a stable state as selected several example.

Table 1. Vehicle recognition rate using neural network

PCU / Signature	small car	bongo	truck(2.5 ton)	large car(Bus)	truck(11 ton)
ORIGINAL Input Data	0000000000 0000010000 0001010000 0001010000 1110001111	0000100000 0001010000 0010001000 0100000100 1000000011	0010000000 0001000100 0101111010 0100000010 1000000001	0000100000 0001010000 0101010010 0010001100 1000000001	0000100000 0001011100 0010000010 0100000010 1000000001
Target Pattern	10000	01000	00100	00010	00001
TEST Signature	Recognition Rate	Recognition Rate	Recognition Rate	Recognition Rate	Recognition Rate
0000000000 0000100000 0000010000 0001000000 0100001010	91 %	14 %	5 %	8 %	1 %
0000100000 0001010000 0000000000 0100000100 0000000001	1 %	93 %	23 %	35 %	3 %
0000000000 0001000100 0101101010 0000000000 1000000001	2 %	3 %	95 %	9 %	2 %
0000100000 0001000000 0101010010 0000000100 1000000000	4 %	6 5	44 %	92 %	60 %
0000100000 0001011000 0000000000 0100000010 0000000000	2 %	28 %	9 %	7 %	96 %

Computer simulation prove that there is a 91% probability or accuracy that particular vehicle is a small car, 14% that it is a medium sized car, 5 % that it is a small truck, 8% that it is a bus, and 1% that it is a large truck. The probability of the neural network recognizing a particular vehicle pattern however decreases when the speed, weight, or the passing area differs dramatically from the original signature pattern. When this situation occurs, the accuracy of predicting the particular vehicle pattern may decrease substantially. If the probability falls below 70%, then the 27 Fuzzy rules are applied to increase the recognition which pass over the center of the lane or 1/2 or 1/4 lane and different passing vehicle speed.

A. Determine optimal traffic cycle using fuzzy logic

The value of inductance of the occupancy time differs when vehicle dector. Therefore, 27 fuzzy rules for improving recognition rate of 5 different vehicles are used when the vehicle speed falls to a minimum of 5 km/hr or increase to a maximum of 50 kn/hr, the vehicle weight is above 1500kg, and the vehicle loop passing area is less than 50%. To run simulation program using Turbo pascal, In this paper we assumed length of traffic intersection is 100M, the length of a small vehicle is 3-4M, the length of a medium vehicle is 5-6M, and the length of large vehicle is 10-15M. In order to determine optimal traffic cycle. We need 2 loop detectors, weight sensor, pressure sensor, and speed sensor.

In order to improve P.C.U. , in this paper, we used 3 input fuzzy membership function and 2 output fuzzy membership function. The following is the Fuzzy Logic Control of Traffic Signal Light. On the basis of 'RULE BASE' of 'FUZZY MEMBERSHIP' function under each condition, we use MAX-MIN deduction method and center of gravity method as Defuzzyfication method.

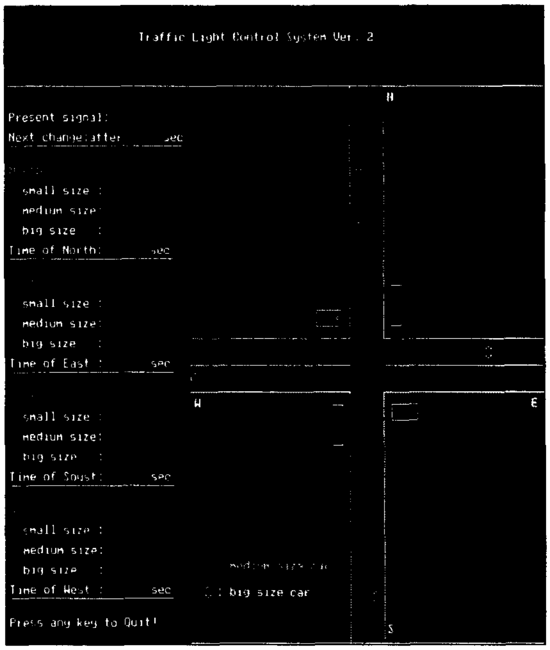

FIg. 3 Simulation of neural fuzzy traffic light

To classify to passenger car unit. To determine

Compare:

Fuzzy traffic signal system ===> Extend to traffic signal cycle

T.O.D. traffic signal system ===> Can not extend to traffic signal cycle

Table 2. Comparisons between fuzzy traffic light depending on road width and conventional traffic light

Road width	P.C.U.		Car speed	Conventional Method		T.O.D. (30SEC)	Fuzzy traffic light		WALK
m	Big	smal	km/ hour	Big	small	waiting time	Big	Small	waiting time
15	3	3	35	12 Sec	9 Sec	9.0 Sec	11.5	9.1	1.6 Sec
30	2	3	33	08 Sec	9 Sec	13.0 Sec	7.5	9.8	0 Sec
40	4	2	38	16 Sec	6 Sec	8.0 Sec	17.2	8.1	5.3 Sec
50	2	3	21	08 Sec	9 Sec	13.0 Sec	8.4	13.8	2.2 Sec
60	3	6	42	12 Sec	18 Sec	0.0 Sec	11.5	18.9	10.4 Sec
70	4	5	43	16 Sec	15 Sec	1.0 Sec	16.2	16.5	4 Sec
100	2	4	21	08 Sec	12 Sec	10.0 Sec	8.3	14.3	2.6 Sec
120	1	7	32	04 Sec	21 Sec	15.0 Sec	3.8	26.1	9.9 Sec

(Assume)

1. Traffic intersection length ....100 METER
2. passing area of LOOP detector 100%

passing Time for Big vehicle

T.O.D. ..... TURN ...4.0 SEC, STRAIGHT ....4.0 SEC,

FUZZY TURN ... 3.5 SEC, STRAIGHT .... 3.3 SEC

passing Time for SMALL vehicle

T.O.D. ..... TURN ...4.0 SEC, STRAIGHT ....4.0 SEC,

FUZZY TURN ... 3.2 SEC, STRAIGHT ....

Table 3. Comparisons between fuzzy traffic light depending on saturation rate and convential traffic light

saturation rate	vehicle speed	Passenger Car Unit			conventional method		Fuzzy traffic light	
%	km/ hour	Big	Medium	Small	T.O.D.	waiting time	WALK	waiting time
83	17	3	1	2	30	07 sec	20	3 sec
71	12	2	2	1	30	11 sec	20	9 sec
85	18	2	0	4	30	10 sec	20	8 sec
62	08	1	2	3	30	4 sec	20	6 sec
55	36	1	1	4	30	6 sec	20	4 sec
34	32	2	2	3	30	12 sec	20	15 sec
47	25	2	1	2	30	10 sec	20	7 sec
38	27	1	2	2	30	17 sec	20	14sec

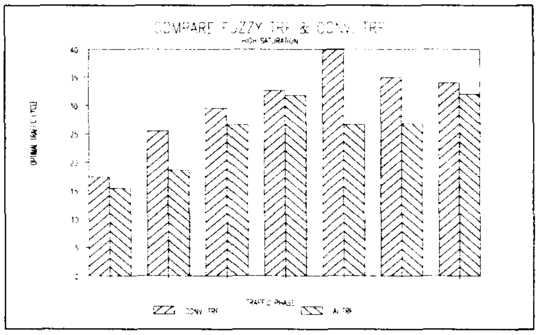

Fig 4 Comparisons between fuzzy traffic light waiting time and high saturation conventional traffic light

Finally, the proposed A.I. traffic controller system has been implemented using look up table method and tested with various types of traffic condition.

V. Conclusion

With the constantly increasing traffic at lighted intersections Neural networks in conjunction with Fuzzy logic will fit extremely well with today's traffic condition.

Remember that the T.O.D. method mentioned relies solely on a predetermined cycling time which remains constant This means that the T.O.D. system can not adjust the green time to the current traffic condition for optimal traffic flow. An electro-sensitive traffic light system was shown that it can extend the traffic cycle when there are many vehicles passing on the road or reduce the cycle if there are few vehicles passing. However, it can not determine which vehicle is long or short. When this happens overflows or the spill back phenomenon occur and increasing waiting time.

On the other hand, we saw that neural networks analyzes each vehicles signature structure (analog data converted to a sampled digital bit pattern) to predict the P.C.U. and to determine the optimal traffic cycle. This means that it can extend or reduce the traffic signal cycle depending on the number of vehicles present. It can also prevent the spill back phenomenon when there are multiple intersectioons close by. Neural networks alone can accurately predict the P.C.U. using the passing vehicle's weight, speed and loop area if the passing vehicles signature matches the test signature data by at least 85%. If none of the test signature fits the vehicle data by at least 70%, then the 27 Fuzzy rules are applied to the vehicles signature to more accurately determine the type of pcu. Once the data is accurately analyzed, the green time is adjusted accordingly to the traffic condition to make for a much smoother flow of traffic.

Next we saw with computer simulation that comparing A.I. traffic light control system versus non fuzzy traffic light system that shortening or extending the traffic cycle taking into consideration the upper traffic condition makes a dramatic difference in waiting time. The conventional method was shown to have a much longer waiting time as well creating spill back since it can not adjust for traffic conditions. Taking all of the above into consideration not only will neural networks with fuzzy logic dramatically reduce vehicle waiting time and increase overall traffic efficiency, but it will also make a dramatic dent in decreasing energy costs.

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