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New Electrosensitive Traffic Light Using Fuzzy Neural Network

You-Sik Hong, Hyunsoo Jin, and Chong-Kug Park

***Abstract*—In the past, when there were few vehicles on the roads, the time-of-day (TOD) traffic signal worked very well. The TOD signal operates on a preset signal-cycling scheme independent of traffic conditions. It cycles on the basis of the number of average passenger cars to the memory device of an electric signal unit. Today, with the increasing traffic and congested roads, the conventional traffic light creates startup-delay time and end-lag time. A 30 to 45% efficiency in traffic handling is lost, as well as added fuel costs, since it is not optimized for today's traffic condition. To solve this problem, an electrosensitive traffic light using neural fuzzy logic will be investigated. This scheme uses an electrosensitive traffic light control, which changes signal based on the passing vehicle's weight, length, and passing area. Through computer simulation, this method has been proven to be much more efficient than fixed time interval signal since the average waiting time, average vehicle speed, and fuel consumption will be improved.**

***Index Terms*—Optimal traffic signal cycle, spillback, vehicle waiting time.**

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You-Sik Hong is with the Department of Computer Science Sangji University, Woosandong, Wonju, 220-702 Korea.
Hyunsoo Jin is with the Department of Electronic Engineering Seoul City University, Seoul, 425-792 Korea.
Chong-Kug Park is with the Department of Electronic Engineering KyungHee University, Suwon, 449-701 Korea.

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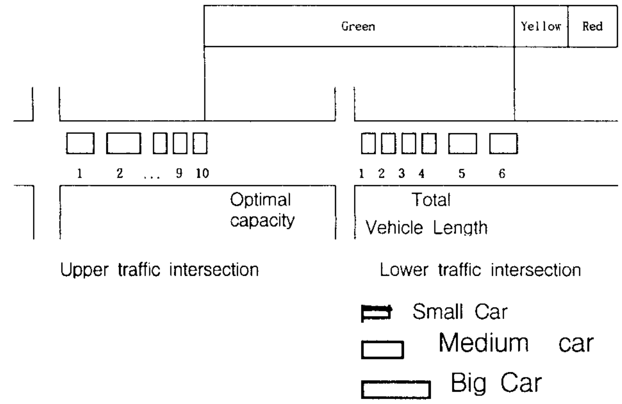

Fig. 1. Green time depending on waiting vehicle—queue 1.

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 has been conducted to optimize traffic flow [4]–[7]. In order to overcome the problems associated with the conventional traffic signal, the traffic signal must reduce the average vehicle waiting time and improve average vehicle speed [8], [9]. The electrosensitive 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, the car waiting time and startup delay time is reduced by using fuzzy control of feedback data. If we improve average vehicle speed by just 10–15%, we will save approximately \$2 000 000 per year. An electrosensitive traffic light system can extend the traffic cycle when many vehicles are on the road or it can reduce the traffic cycle when there is a small number of vehicles on the road. A drawback to just using an electrosensitive traffic light system is that it doesn't consider vehicle length, so overflows may occur if the passing vehicle is long—such as a bus or truck [10]–[12]. 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. In Section II, we briefly explain the problem of a conventional traffic light. Section III presents the basic principle of vehicle and different vehicle analog signature using a loop detector and estimating vehicle length. Section IV describes the determination of the optimal traffic cycle using neural network and fuzzy logic computer simulation. Finally, Section V will give conclusions.

II. Problem Using Conventional Traffic Light

Looking at Fig. 1 there are six vehicles waiting at the lower traffic intersection. At the upper traffic intersection, the traffic condition is such that the degree of saturation is low; thus, all six vehicles can pass to the upper traffic intersection during the green time. Fig. 1, along with Table I, shows that the waiting automobiles consist of four small vehicles and two medium-sized vehicles. From the calculations, all six vehicles may pass to the upper traffic intersection during the green time since the available distance is 30 m and only 28.5 m are required to pass the traffic through. Fig. 2 and Table II show the waiting automobiles consist of three large vehicles and three medium sized vehicles. In this case, only the first three vehicles may pass

TABLE I
(a) WAITING QUEUE LENGTH CONSISTING IN SMALL–MEDIUM VEHICLES AT THE LOWER TRAFFIC INTERSECTION. (b) OPTIMAL GREEN TIME DEPENDING ON NUMBER OF VEHICLES

passing cars	length	Passenger Car Unit
1 (small)	4 meter	1.3
2 (small)	4 meter	1.3
3 (small)	4 meter	1.3
4 (small)	3.5 meter	1.2
5 (med)	6 meter	1.5
6 (med)	7 meter	1.6

(a)

Number of Vehicles	T.O.D.	Optimal Green Time	Vehicle Waiting Time
Small : 4 Medium: 2 Large :	30 Sec	4•3=12 sec 2•3.5= 7 sec Total 19 Sec	T.O.D. - Optimal Green Time = 30 - 19 = 11 Sec
Small : 1 Medium: 3 Large : 2	30 sec	1•3= 3 sec 3•3.5=9.5 Sec 2•4= 8 Sec 20.5 Sec	T.O.D. - Optimal Green Time = 30 - 20.5 = 9..5 Sec

(b)

to the upper traffic intersection during the green time since the total distance required for the three vehicles is 29 m. If all six vehicles were to pass to the upper intersection, a spillback would be created since a minimum distance of 48.5 m would be required to hold the vehicles. A detailed description is presented in Section IV describing how to prevent this spill back phenomenon from occurring.

In Fig. 1, there are no large vehicles and no occurrence of spillback phenomenon.

In this paper, assume that it takes 3 s for a small car and 4.2 s for a large car to pass through a crossroad. Moreover, large car left-turn departure time is 1.3 s 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 (Table I) and spillback phenomenon, we must know how many vehicles come in the traffic intersection and if the vehicle is small or large. Therefore, in this paper, we proposed fuzzy neural traffic light will improve average vehicle speed and spillback phenomenon.

In Fig. 2, upper traffic intersection is highly saturated, the waiting vehicle is larger than the approach road, spillback is generated at one signal, and traffic congestion occurs at the next traffic signal.

III. PRINCIPLE OF VEHICLE DETECTING

The conventional loop detector installed on roads today detect a change in inductance from the presence of a vehicle. The loop sensitivity (SL) of an inductive loop is defined as

$$\mathrm{SL} = 100 \star \frac{\mathrm{LNV} - \mathrm{Lv}}{\mathrm{LNV}} = 100 \star \frac{\Delta L}{L} \tag{1}$$

where

LNv inductance with no vehicle;
Lv inductance with vehicle.

Vehicle detector systems sense a decrease in inductance during the passage or presence of a vehicle in the zone of detection of the sensor

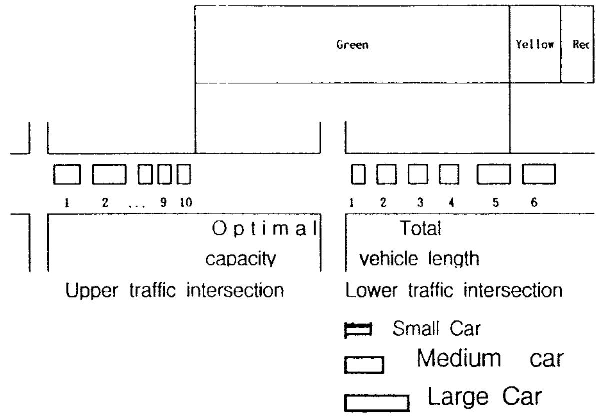

Fig. 2. Green time depending of vehicle waiting—queue 2.

TABLE II
WAITING QUEUE LENGTH CONSISTING ON SMALL–MEDIUM–LARGE VEHICLES AT THE LOWER TRAFFIC INTERSECTION

passing cars	length	Passenger Car Unit
1 (small)	4 meter	1.3
2 (med)	6.5 meter	1.5
3 (med)	6 meter	1.5
4 (med)	7 meter	1.6
5 (Large)	12 meter	1.7
6 (Large)	13 meter	1.8

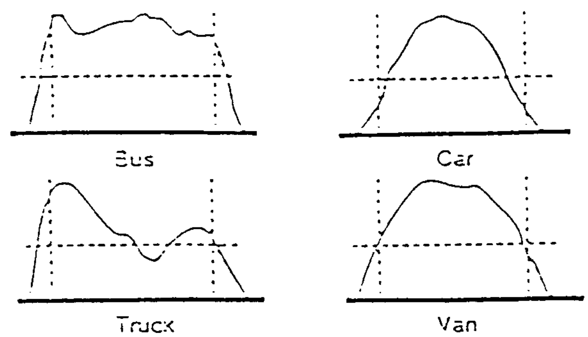

Fig. 3. Different vehicle analog signature using loop detector.

loop. Thus, when a vehicle passes over the loop or stops within the loop, the inductance of the loop decreases.

The inductance may vary depending on three factors which include vehicle speed, vehicle weight, and passing area of loop detector. For example, when an approaching vehicle from the lower intersection passes over the loop detector the inductance may vary as shown

- Class 1) 1.13% $(\triangle L/L)$ or 1.12 μh $(\triangle L)$ inductance change (small vehicle);
- Class 2) 2.36% $(\triangle L/L)$ or 2.13 μh $(\triangle L)$ inductance change (medium vehicle);
- Class 3) 3.49% $(\triangle L/L)$ or 3.27 μh $(\triangle L)$ inductance change (large vehicle).

In Fig. 3, sensitivity for four classifications of analog vehicle signature have specific values, when they pass the single loop detector (1.8 m $\star$ 1.8 m). But, it is not the same passing vehicle speed, passing vehicle weight, and passing area of loop detector when lower traffic intersection of passing vehicles passes over the loop detector. Therefore, it is not easy to classify four kinds of passenger car units.

To determine passenger car unit using loop detector, weight sensor, and pressure sensor, as shown in Fig. 3. The passenger car unit is taken from loop detector placed on the road, 25 m before the traffic

TABLE III
DETERMINING RULE OF PASSENGER CAR UNIT

Speed Sensor	Vehicle Speed	3 Km/hr < speed < 10Km/hr 11 Km/hr < speed < 30Km/hr 21 Km/hr < speed < 50Km/hr
Loop Detector	Passing Area	Line 1/4 1/2
Weight Sensor	Vehicle Weight	450 Kg < Weight < 850Kg 851 Kg < Weight < 1300Kg 1301 Kg < Weight < 3000Kg

TABLE IV
PCU FOR APPROACHING VEHICLE

Car \ Phase	1	2	3	4	5
Phase 1	1.3	1.2	1.2	1.5	1.3
Phase 2	1.2	1.4	1.6	1.2	1.3
Phase 3	1.2	1.2	1.9	1.4	1.7
Phase	1.6	1.8	1.9	1.2	1.9

TABLE V
PCU FOR APPROACHING VEHICLE

From \ To	1	2	3	4	5
Phase 1	6.5	5.6	5.6	8.7	6.3
Phase 2	5.6	6.8	9.6	5.6	6.3
Phase 3	5.6	5.6	14.3	6.8	10.5
Phase 4	9.6	12.8	14.6	5.6	14.8

TABLE VI
PASSING VEHICLE OF EXPECTING PCU 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

light and three fuzzy input membership function and 27 fuzzy logic control rules are used to determine the optimal traffic cycle.

A. Estimating Waiting Vehicle Length

If the approaching vehicle speed is 20 km/h, total weight is 1500 kg, and passing area of loop detector is 80%, it can be written as

$$\begin{aligned}&\text{Passenger car unit} = \text{Veh(spd)}, \text{Veh(pwr)}, \text{Veh(twt)}\\ &\text{Expecting vehicle length} = 12\text{ m.}\end{aligned} \tag{2}$$

If the approaching vehicle speed is 5 km, total weight is 550 kg, and passing area of loop detector is 80%, it can be written as

$$\begin{aligned}&\text{Passenger car unit} = \text{Veh}(1/4\text{ spd}), \text{Veh(pwr)}, \text{Veh}(1/3\text{ twt})\\ &\text{Expecting vehicle length} = 5\text{ m.}\end{aligned} \tag{3}$$

Small vehicle	Small Bus
0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0	0 0 0 1 1 1 1 0
0 0 0 0 1 0 0 0	0 1 0 0 0 0 1 0
0 0 0 1 0 1 0 0	1 0 0 0 0 0 1 0
0 1 1 0 0 0 1 1	1 0 0 0 0 0 0 1

Large Bus	Small Truck	Large Truck
0 1 1 1 1 1 1 0	0 0 0 0 0 0 0 0	0 0 1 0 0 0 0 1
0 1 0 0 0 0 1 0	0 0 0 1 0 0 0 1	0 1 0 1 0 0 0 1
0 1 0 0 0 0 1 0	0 1 1 0 1 0 1 1	0 1 0 0 1 0 1 1
1 0 0 0 0 0 1 0	0 1 0 0 0 1 1 1	0 1 0 0 0 1 0 1
1 0 0 0 0 0 0 1	1 0 0 0 0 1 0 1	1 0 0 0 0 1 0 1

Fig. 4. 5 Kinds of vehicle input data.

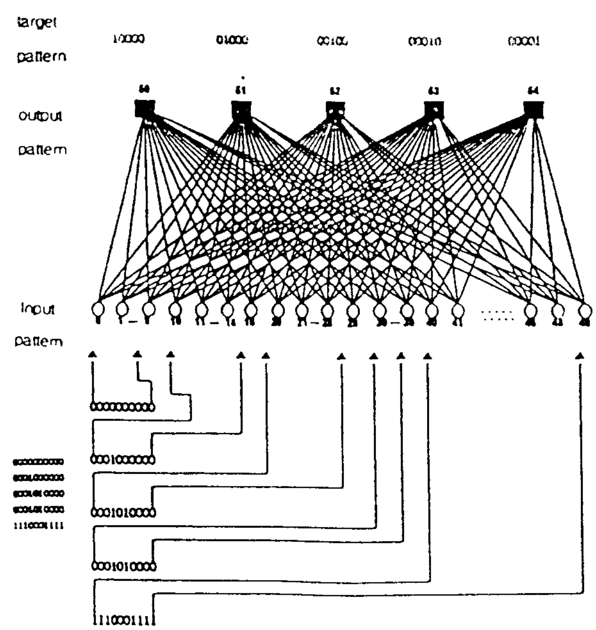

Fig. 5. Neural network structure for vehicle classification.

If approaching vehicle speed is 10 km/hr total weight is 550 kg, and passing area of the loop detector is 40%, it can be written as

$$\begin{aligned}&\text{Passenger car unit} = \text{Veh}(1/2\text{ spd}), \text{Veh}(1/2\text{ pwr}), \text{Veh}(1/3\text{ twt})\\ &\text{Expecting vehicle length} = 6.5\text{ m.}\end{aligned} \tag{4}$$

In Table IV, there are five vehicles on the road. But the passenger car unit is different. Therefore, we will rewrite for vehicle length in Table V. Finally, sum of approaching vehicle length in phase 1–phase 4 is shown in Table VI.

As you can see in Figs. 1 and 2, to solve spillback phenomenon we must calculate number of passing vehicles using the loop detector and determine which car is big or small.

Therefore, in this paper, to prevent overflow and reduce average vehicle waiting time at the intersection, we propose on optimal traffic cycle using fuzzy rules and neural network.

TABLE VII
VEHICLE RECOGNITION RESULT USING NEURAL NETWORK

PCU / Signature	small car	Medium car (Bongo)	Medium Car truck (2.5 ton)	Large Car (Bus)	Large Car Truck (11ton)
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 %

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 nonexistence of supervised signal. We use a supervised learning process, which adjusts weights to reduce the error between desired output and real output. This is depicted as follows:

1) initialize weights and offset;
2) establishment of training pattern;
3) compute the error between target pattern output layer neural cell (t_j) and output layer neural cell (a_j)

$$e_j = t_j - a_j \tag{5}$$

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

$$W(\text{new})_{ij} = W(\text{old})_{ij} + \alpha e_{ia j} \tag{6}$$
$$e_j = t_j - a_j \tag{7}$$

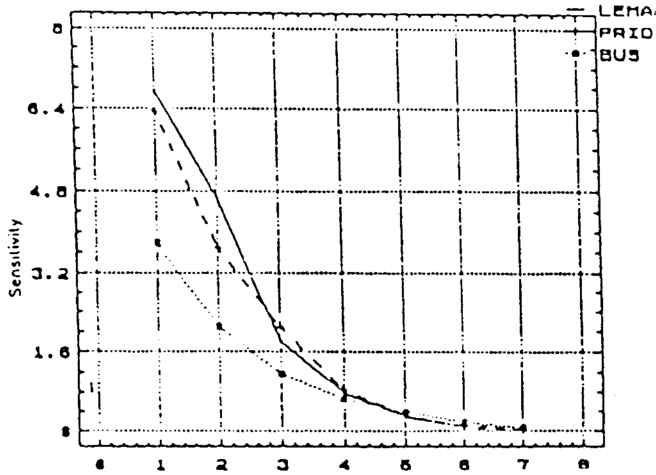

Fig. 6. Loop detector character depending on passing area.

5) repeat the process from 2) above; process is repeated until all weights reach a stable state as selected from several examples.

The training algorithm and neural network structure used in this paper is as follows:

1) initialize weights and offset;
2) present input and desired output;
3) input signal form data 0 is a studied supervised signal conforming to target pattern 10 000, which is a supervised signal; input signal form data 1 is a studied supervised signal conforming to target pattern 01 000, which is a supervised signal input signal form; data 2 is a studied supervised signal conforming to target pattern 00 100 which is a supervised signal; input signal form data 4 is a studied supervised signal conforming to target pattern 00 001 which is a supervised signal;
4) calculate connection weights and active value to each unit (Shown at the bottom of the page)

error error of neural network with respect to the input pattern p;
Op0 real output of jth neural cell of output layer with respect to the input pattern p;
tp0 jth factor of target pattern p.

5) When trained pattern of five results 300 times, the calculated error is 0.345 123 1 and data accuracy is above 97%.

Fig. 4 shows digital representation of different types of vehicle analog signature. All the analog signature pattern (as shown in Fig. 3) are sampled to get the digital bit pattern so that the data may be used for vehicle recognition using neural network.

Fig. 5 shows how the data in Table VII was derived. Each row of the test signature bit pattern (10 bits $\star$ 5 bits) is compared to the same row of the original input data which is based on normal values for speed, weight, and loop area in each class. After all 5 rows $\times$ 10 bits wide are compared, the neural network determines the probability or accuracy of a vehicle test pattern being in that class. As shown in Table VII, the first test signature pattern shows that there is a 91% probability or accuracy that a particular vehicle is a small variation: 14% that it is a medium sized car; 5% that it is a small truck; 8% that

$$\text{error}\, p = \sqrt{(\text{Op}0 - \text{tp}0)^2 + (\text{Op}1 - \text{tp}1)^2 + \cdots + (\text{Op}n - \text{tp}n)^2}$$
$$= \sqrt{\sum_{i=j}^{i=p} (\text{Op}_{ij} - \text{tp}_{ij})^2}$$

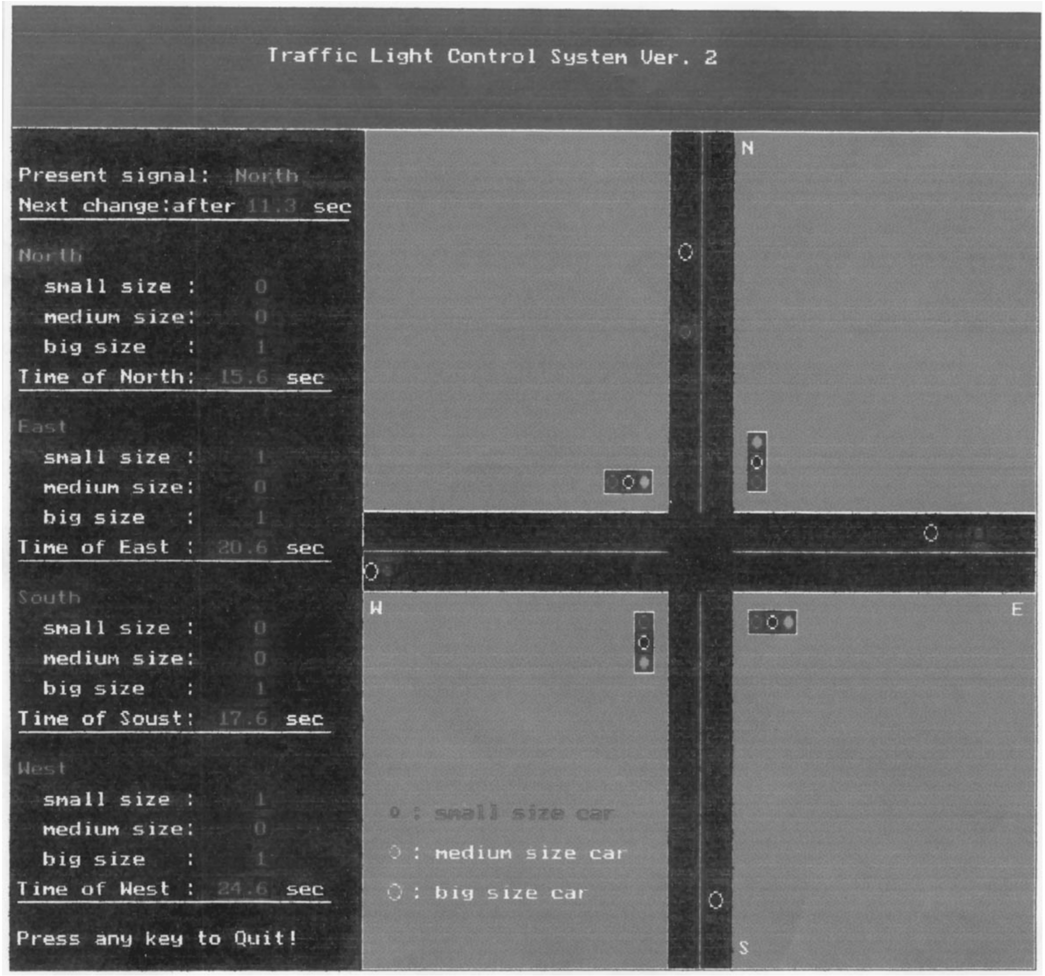

Fig. 7. Fuzzy traffic light simulation one.

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 accuracy of predicting the correct type of vehicle.

The input layer neuron (neural cell) is 49 pieces from number zero and the output layer neuron (neural cell) is 50 pieces from number 55. The neural cell of the network is 55 pieces from number zero. The connection of the network is 500 pieces from number zero. The layer of network is two pieces from number zero and the training rule of network used the delta rule.

In basic traffic-actuated control, the minimum green interval depends on the number of cars that are stored in the loop counter. When the number of vehicles are known, the minimum green interval can be calculated. Unfortunately, it is very difficult to determine whether the vehicle passing through the loop detector which vehicle is large or if the time differs when vehicles pass over the center of the lane or $1/2$ or $1/4$ of the lane at different passing vehicle speed. Therefore, these problems can make errors in the recognition rate of vehicles. To improve the recognition rate for vehicles, it consequently uses 27 fuzzy rules.

A. Determine Optimal Traffic Cycle Using Fuzzy Logic

The value of inductance of the occupancy time differs when vehicles pass over the center of the lane or $1/2$ or $1/4$ lane and different passing vehicle speed as shown in Figs. 6 and 7. Moreover, real traffic conditions may vary substantially from the normal values for vehicle speed, weight, and passing area of loop detector. Therefore, using 27 fuzzy rules will improve recognition rate of five different vehicles used when the vehicle speed falls to a minimum of 5 km/h or increase to a maximum of 50 km/h the vehicle weight is above 1500 kg and the vehicle loop passing area is less than 50%. To run the simulation program using Turbo pascal, in this paper we assumed length of traffic intersection is 100 m, the length of a small vehicle is 3–4 m, the length of medium vehicles 5–6 m, and the length of large vehicle is 10–15 m. In order to determine optimal traffic cycle, need two loop detectors, a weight sensor, a pressure sensor, and a speed sensor.

1) Check in detector: placed just behind the traffic light, it is used to count the number of on coming vehicles by terminated turns with green after minimum red. It increments a counter every time a vehicle passes over the loop detector.
2) Check out detector: placed behind the 75 m traffic light, it is used to count the number of outgoing vehicles terminated turns with green after minimum red. It decreases a counter every time a vehicle passes over the loop detector.
3) Weight sensor: placed well in advance of check out detector, it is used to determine vehicle weight.
4) Pressure sensor: placed well in advance of check out detector, it is used to determine passing area of loop detector.
5) Speed sensor: placed well in advance of check out detector, it is used to determine passing vehicle speed.

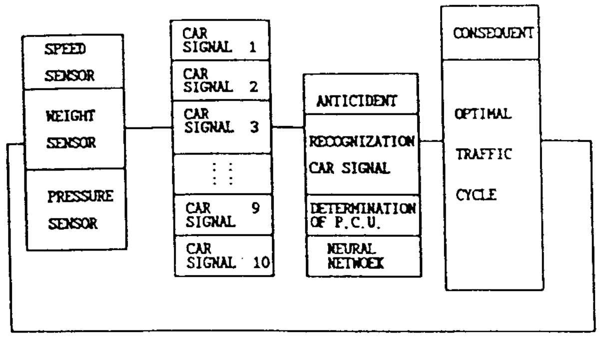

Fig. 8. Block diagram of neural fuzzy traffic light.

In order to improve PCU, in this paper, we used three input fuzzy membership function and two 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 the defuzzyfication method.

High saturation rate (upper traffic intersection)

IF TPR is HIGH
and TSP is MED
and TWT is SMALL then
Op is HIGH
Os is HIGH

TPR is the passing area of loop detector
RSP is the passing vehicle speed
TWT is the total weight vehicle
OP is the expecting passenger car unit
OS is the expecting passenger car speed

Optimal traffic cycle $=$ Expecting car speed (OS) $\star$ Number of cars $\star$ Expecting passenger car unit (op)

Low saturation rate (upper traffic intersection)

IF TPR is HIGH
and TSP is MED
and TWT is HIGH
Op is HIGH
Os is Med

TPR is the passing area of loop detector
TSP is the passing vehicle speed
TWT is the total weight vehicle
OP is the expecting passenger car unit
OS is the expecting passenger car speed

To determine passenger car unit in this paper, use the loop detector, weight sensor, and pressure sensor. The passenger car unit is taken from loop detector placed on the road 25 m before the traffic light and three fuzzy input membership function and 27 fuzzy logic control rules are used to determine optimal traffic cycle (Fig. 8).

The determination of the vehicle speed, vehicle weight, and passing area of loop detector are the most important factors in recognizing different vehicle size (passenger car unit).

Three types of problems that cause mistakes to occur include changes in car weight, car speed, and passing area. It is very difficult when vehicles pass over the center half or quarter at varying speeds. Because of these factors, three fuzzy input membership functions

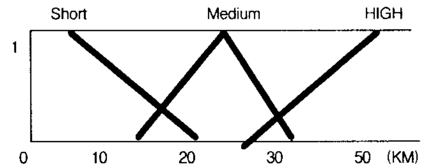

Fig. 9. Input fuzzy membership function for vehicle speed.

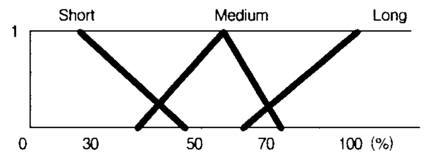

Fig. 10. Input fuzzy membership function for passing area.

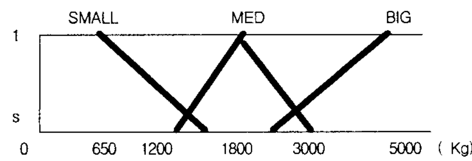

Fig. 11. Input fuzzy membership function for vehicle weight.

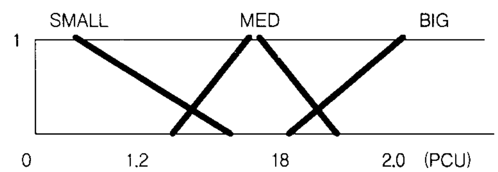

Fig. 12. Output fuzzy membership function for expecting PCU.

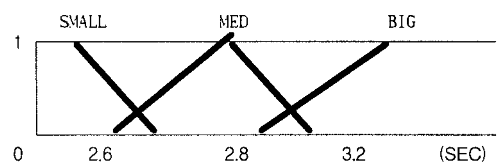

Fig. 13. Output fuzzy membership function for expecting vehicle speed.

and fuzzy 27 rules are used to determine optimal traffic cycle. Fuzzy membership functions are organized as follows. The first fuzzy input membership function for vehicle speed is illustrated in Fig. 9. They have three membership functions described by kilometers per second: short, medium, and long. The second fuzzy input membership function for passing areas of loop detector can be illustrated in Fig. 10. They have three membership functions describing by percentage of passing area: short, medium, and long. The third fuzzy input membership function for vehicle weights is illustrated in Fig. 11.

They have three membership functions describing the weight: short, medium, and long. The output of the fuzzy traffic controller estimate passenger car unit and expecting vehicle speed. The first output membership function for passenger car units is shown in Fig. 12. This will determine which vehicle is small, medium, or large. The second output membership function for optimal vehicle speed is shown in Fig. 13. This will determine whether to extend, reduce, or keep the green time constant.

The passenger car unit is taken from a loop detector placed on the road, 25 m before the traffic light and three fuzzy input membership function and 27 fuzzy logic control rules used to determine optimal traffic cycle (Fig. 14).

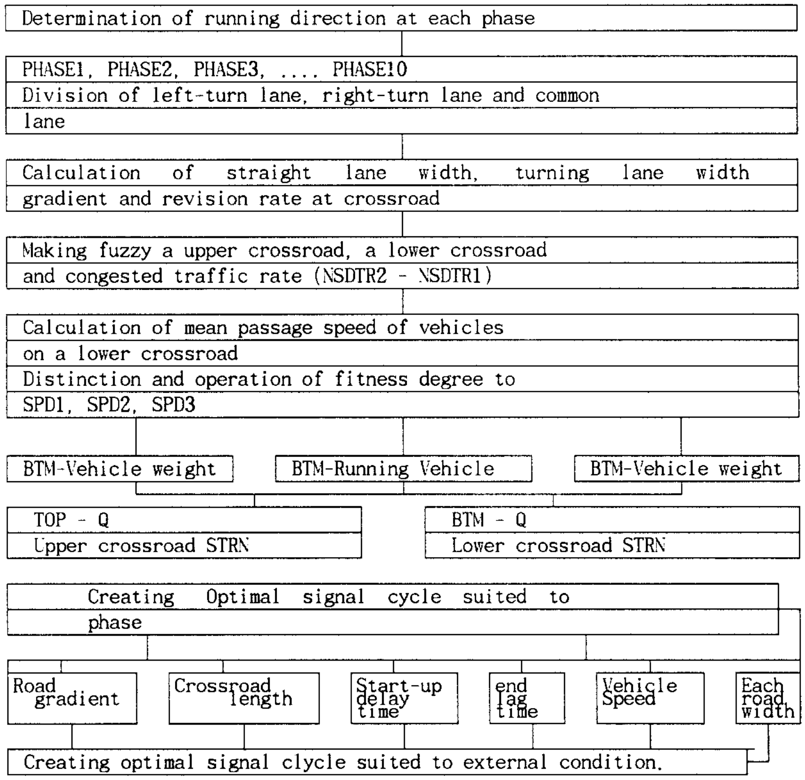

Fig. 14. Flowchart of fuzzy traffic light signal light.

TABLE VIII
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	small	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
65	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

TABLE IX
COMPARISONS BETWEEN FUZZY TRAFFIC LIGHT DEPENDING ON SATURATION RATE AND CONVENTIONAL 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

B. Computer Simulation Result

A comparison with an artificial intelligence (AI) traffic light considering passenger car unit of vehicle waiting time and a nonfuzzy traffic light waiting time is shown in Tables VIII and IX. The advantage of the new electrosensitive traffic light based on neural fuzzy traffic controller is shown as follows.

Traffic condition 1 Expected passing vehicle numbers from lower traffic intersection are large and saturation rate from upper traffic intersection approaches a high level. Compare fuzzy traffic signal system ⇒ Shorten to traffic signal cycle time-of-day (TOD) traffic signal system ⇒ cannot shorten to traffic signal cycle.

Traffic condition 2 Expecting passing vehicle numbers from lower traffic intersection are small and saturation rate of upper traffic intersection approaches a low level. Compare fuzzy traffic signal system ⇒ Extend to traffic signal cycle (TOD) traffic signal system⇒Cannot extend to traffic signal cycle.

Figs. 15 and 16 show comparison of waiting time of fuzzy traffic light and conventional traffic light. For the fuzzy neural traffic controller, the average waiting time decreased by 15% when compared with the conventional controller.

Finally, the proposed AI traffic controller system has been implemented using the lookup table method and tested with various types of traffic condition.

Fig. 17 shows the block diagram of fuzzy hardware traffic light. The operation of hardware using fuzzy lookup table method is as follows.

In order to create optimal green time, it will get input fuzzy value for total vehicle speed (TSP), total average vehicle pressure (TPR), total average vehicle weight (TWT), and the number of expecting passing vehicles using loop detectors that are installed on the road.

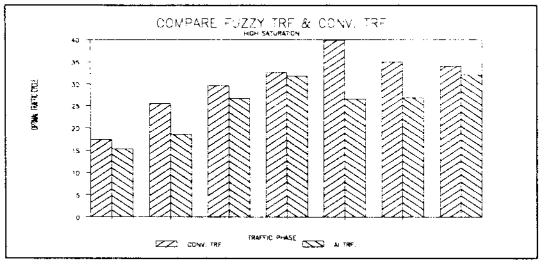

Fig. 15. Comparisons between fuzzy traffic light waiting time and high-saturation conventional traffic light.

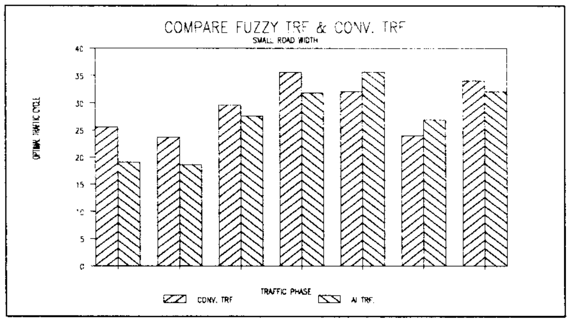

Fig. 16. Comparisons between fuzzy traffic light waiting time and low-saturation conventional traffic light.

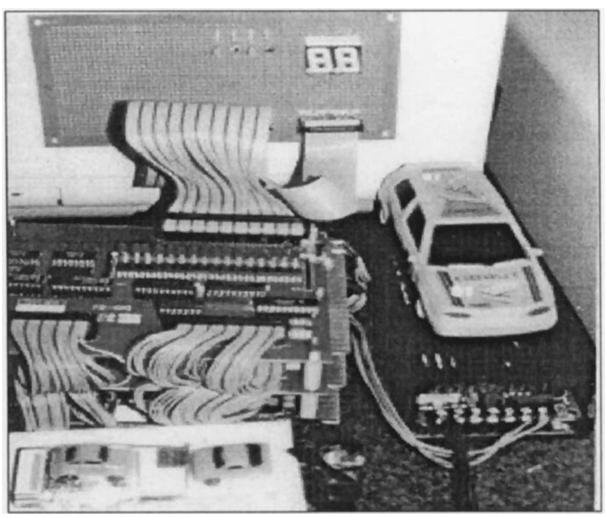

Fig. 17. Implementation neural fuzzy traffic light.

Fuzzy traffic hardware seeks for the fuzzy lookup table accumulating the inferenced data, which is stored in RAM for output expecting passenger car unit and expecting speed.

Fuzzy traffic hardware selects best optimal green time, which stores 27 fuzzzy rules.

Optimal green time can be calculate with following rule. Green time rule $=$ op $\star$ os $\star$ number of passing vehicles; op is optimal expecting passenger car unit and os is optimal vehicle speed.

The number address of fuzzy hardware lookup table method is a crisp value that inferenced input membership function which is stored in RAM block.

This RAM can process the 27 fuzzy rules. The rule and input data are composed of 4 bit data.

Fig. 18 shows the block diagram of defuzzification for fuzzy traffic hardware.

INPUT				OUTPUT	
	TSP	TPR	TWT	OP	OS
0000	1-20	1-30	400-1000	1.5	3.0
0001	1-20	31-60	400-1000	1.3	3.0
0010	1-20	61-100	400-1000	1.2	2.8
0011	1-20	1-30	400-1000	1.5	3.0
0100	1-20	31-60	400-1000	1.3	3.0
0101	1-20	61-100	400-1000	1.2	2.8
0110	41-60	1-30	400-1000	1.5	3.0
:	:	:	:	:	:
11000	41-60	1-30	2001-4000	1.7	3.0
11001	41-60	31-60	2001-4000	1.6	3.2
11010	41-60	61-100	2001-4000	1.9	3.5

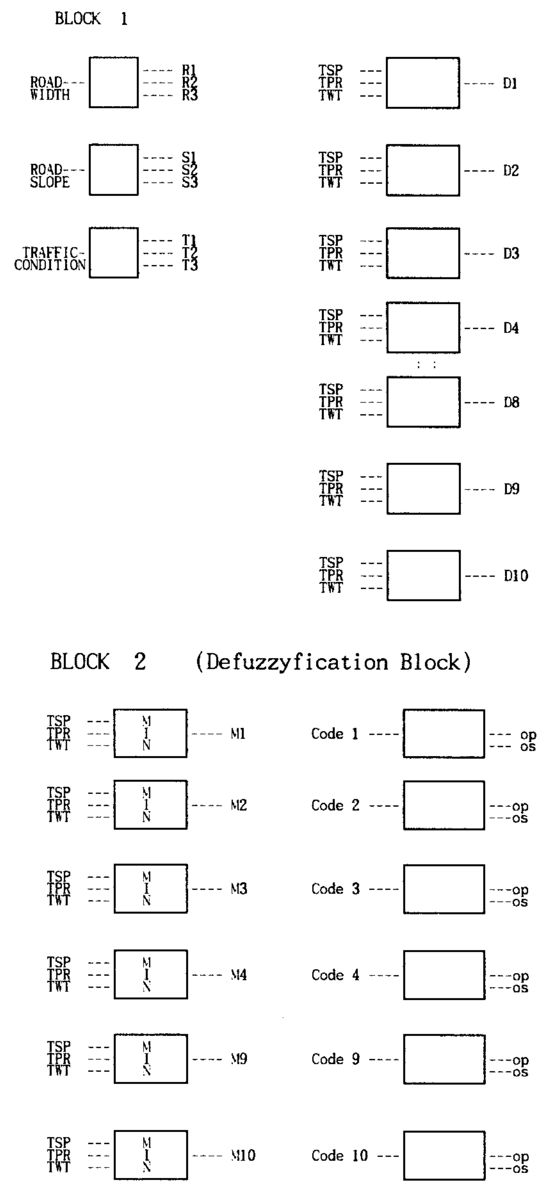

Fig. 18. Block diagram of fuzzy traffic light using lookup table.

The advantage of the proposed method is that it can be implemented without divider and multiplier.

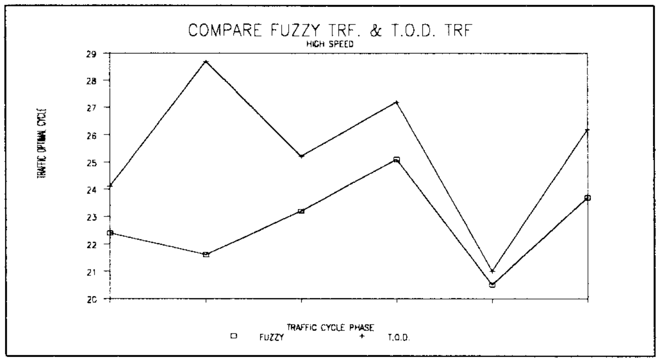

Fig. 19. Comparisons between fuzzy traffic light waiting time and conventional traffic light.

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 TOD method mentioned relies solely on a predetermined cycling time, which remains constant. This means that the TOD system cannot adjust the green time to the current traffic condition for optimal traffic flow. An electrosensitive traffic light system has 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 cannot determine which vehicle is long or short. When this happens, overflows or the spillback phenomenon occurs as well as resulting increased waiting time.

On the other hand, we saw that neural networks analyzes each vehicle's signature structure (analog data converted to a sampled digital bit pattern) to predict the PCU 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 spillback phenomenon when there are multiple intersections close by. Neural networks alone can accurately predict the PCU 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 an AI traffic light control system versus nonfuzzy traffic light system that shortens or extends 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 as 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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Comments on "Choquet Fuzzy Integral-Based Hierarchical Networks for Decision Analysis"

A. Köksal Hocaoğlu and Paul Gader

***Abstract*—We remark on an error in the above paper. The purpose of this note is to present the correct formulas for partial derivatives of fuzzy integral-based neural nodes with respect to densities of Sugeno measures.**

***Index Terms*—Fuzzy integral, fuzzy measure.**

I. Introduction

In a recent article,[1] Choquet fuzzy integrals are proposed to form the node activation functions for hierarchical networks for decision analysis. Sugeno measures are used. Densities are learned using a gradient descent algorithm.

As noted in [1], the node output f is given by

$$f = \sum_{i=1}^{m} h(x_i) g_i (1 + \lambda g(A_{i+1})).$$

The partial derivative of f with respect to g_j given in the paper is not correct. The problem is that the parameter λ is also a function of the densities and so its partial must be included in the derivation. Notice that according to (12) in the above paper, the partial derivative of f with respect to a density is always nonnegative. This is not the case for the Sugeno measure. There are cases for which the derivative is negative.

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The authors are with the Department of Computer Engineering and Computer Science, University of Missouri-Columbia, Columbia, MO 65211 USA.

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