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Fuzzy Q-Learning Traffic Light Control based on Traffic Flow and Pedestrian Number Estimated from Visual Information

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Abstract: A vision-based intelligent traffic control system is a robust framework that controls the traffic flow in real-time by estimating the traffic density near traffic lights. In this paper, a traffic light control system based on fuzzy Q-learning is proposed according to the vehicle density and the pedestrian number estimated from the visual information. The aim of proposed approach is to minimize the pedestrian and the car waiting time and maximize throughput for an isolated 4-way traffic intersection. Also, the pedestrian traffic light is controlled based on the fuzzy logic. The states and actions of the Q-learning variables are set by a fuzzy algorithm which can be learned through environmental interactions. The system can detect the number of pedestrians and vehicles using visual information from cameras and machine vision algorithms. The fuzzy control system can adjust the sequence of green phases to decrease the total waiting time and the mean of the queue length. The proposed algorithm was simulated for one hour for each of 14 different traffic conditions and was assessed and compared with the preset cycle time and vehicle actuated approaches. The results showed the proposed algorithm could decrease the total waiting time and the mean of the queue length effectively.

Keywords. Intelligent traffic control system, Traffic density, Fuzzy logic, traffic light control.

1. Introduction

Many big cities are confronted with heavy traffic because of the ever-increasing population and the limitation of the existing resources in the current infrastructures. As a result, efficient methods for traffic flow management are necessary to optimize the use of the available road capacity. High fuel prices and environmental problems are the other important reasons to reduce traffic.

Most of the existing studies have not considered the impact of pedestrian density on the traffic light duration, and none of them have exclusively controlled the role of pedestrian traffic lights. Some studies have investigated the pedestrian density at the end of each phase to calculate the next green phase duration. These approaches cannot work in unpredictable environments such as intersections near the subway or BRT stations because the pedestrian number during the green phase is not predictable based on the previous phase. In multi-agent traffic light control in which small groups of closely spaced lights communicate with one another to cycle synchronously, the coordination mechanism cannot maintain synchronization because unpredictable pedestrian passing during the green phase of traffic light disturbs the vehicle passing, and the system cannot synchronize the intersections with one another based on the traffic following model. Adjusting pedestrian traffic light duration separately in the critical situations can resolve this problem because it prevents the pedestrian crossing during the vehicles' green light. Therefore, the need arises for optimizing traffic control systems that can adapt to this increasing congestion. This study attempts to decrease the traffic congestion through the development of an intelligent traffic control system based on the traffic density flow at intersections.

Many investigations have attempted to solve different traffic problems in the intelligent transportation systems [1, 2, 3, 4, 5]. In many cases, a fixed time traffic light control system has been used with the aim of minimizing the waiting time and the number of vehicles waiting at intersections. However, it is preferable to have dynamic traffic light control systems in which the green light duration is adjusted based on the dynamic environmental changes to maximize throughput and minimize the waiting time. Fuzzy control systems use fuzzy logic, which simulates the human intelligence to control traffic and enables the implementation of real-world rules and human-like thinking process. Fuzzy control is an approach that can be applied to various traffic models. The fuzzy logic traffic light controllers utilize sensors to count the number of vehicles. Therefore, the resulting controllers control the traffic lights according to traffic density [6]. There are different approaches to control traffic lights based on the artificial intelligence methods such as fuzzy logic, neural networks, reinforcement learning, and evolutionary algorithms. These methods can lead to shorter queues and less traffic delays.

There are two approaches to traffic light control including pre-timed [7] and sensor-based signal controls. The preset cycle time methods present the traditional strategy which consists of a preset interval series that cannot respond to the unpredictable conditions and a waste of time for the less congested roads [8]. The vehicle actuated methods are sensor based methods in which the green light time can be extended based on a demand.

To overcome the mentioned problems and to reduce the waiting time and the queue length, this paper proposes a Q-learning fuzzy controller which is based on the traffic density

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and the pedestrian number. We propose a two-phase real-time approach, first, based on fuzzy Q-learning for adjusting the traffic light duration and second, the fuzzy control for the pedestrian traffic light duration for an isolated intersection based on the visual information. Compared to the pre-set cycle time (PCT) and the vehicle actuated approaches, the proposed method can reduce the average number of vehicles in traffic queues and the average waiting time for vehicles. Also, the proposed method can decrease the pedestrian waiting time significantly. The proposed system can analyze the various relationships between traffic conditions and the optimal actions using its experience in different situations. Furthermore, it can effectively work in specific situations based on its experience with identical or similar situations. There are some potential actions; each state is related to its corresponding action via fuzzy if-then rules. The proposed algorithm takes the advantages of fuzzy logic and Q-learning approaches by tunning fuzzy inference parameters for each fuzzified state using Q-learning.

The advantages of the proposed approach are as follows:

• No need for the pre-specified models as training is possible for any traffic conditions

• Can learn the relationships between states and actions using environmental interactions

• Benefits from the fuzzy system advantages which avoid discretization problem of Q-learning by dealing with continuous states and actions

• Suitable for synchronization

The rest of this paper is organized as follows. A summary of the background work is presented in section 2. Section 3.1 reviews the local binary pattern and Gabor filters and the pedestrian number estimation method. Section 3.2 reviews the Gaussian mixture model and presents the vehicle number estimation scheme. Section 3.3 reviews fuzzy Q-learning and presents the algorithm scheme. Section 4 reports experimental results and section 5 concludes the paper.

2. Background

As this paper aims to improve the traffic light control, the existing methods on this subject are briefly discussed below.

Smith et al. proposed a neural network based on the approach for the traffic light control. This approach has a time-consuming learning process and reduces the waiting time by 10% [9]. The use of fuzzy logic results in a good performance in traffic congestion control [10, 11]. Arora et al. measured traffic density on the road using morphological edge detection and a fuzzy logic technique [12]. Tari et al. used a two-level hierarchical fuzzy rule-based system for controlling complex traffic intersections [13]. Keyarsalan et al. used computer vision techniques and neural networks to extract the traffic data and apply a fuzzy ontology to control the traffic lights in the isolated intersections [6]. Shakeri et al. introduced a three-layer fuzzy system based on the cellular automata for optimizing the traffic light control [14]. Abdulhai et al. provide an isolated traffic signal controller using reinforcement learning which could be combined with dynamic route guidance [15]. Also, multi-agent Q-learning was used for a non-stationary environment that estimated states based on the average queue length [16]. In order to minimize the waiting time of the public transportation and reduce the computational complexity, dynamic programming and branch-and-bound techniques were combined to control traffic lights [17].

Liu et al. presented a differential evolution bacteria foraging optimization algorithm to minimize the vehicles' delay in a cycle and maximize throughput of the intersection [18]. In another work, vehicles were detected using edge detection and matching. After the edge detection, the reference and the real-time images were matched and the traffic light duration was determined based on the percentage of matching of the two images [19].

Dujardin et al. applied Mixed Integer Linear Programming (MILP) for multimodal traffic light control based on the optimization of three criteria including the total delay of persons and public vehicles, and the number of stops for the private vehicles [20]. Jalali Moghaddam et al. proposed a two-phase real-time traffic light control system based on fuzzy q-learning for adjusting traffic light duration for an isolated 4-way intersection based on the traffic flow [21]. Bazzan et al. investigates the task of multi-agent reinforcement learning for the control of traffic signals [22]. Mikami et al. proposed a cooperative signal control scheme with a combination of genetic algorithm and reinforcement learning [23]. Rezzaii et al. proposed a multi agent reinforcement learning based the algorithm for the traffic light control [41, 42]. Zhu et al. modelled traffic signals as intelligent agents interacting with the stochastic traffic environment to develop the Junction Tree Algorithm (JTA) based on the reinforcement learning for the coordinated signal control problem [24].

Cesme et al. explored a new model based on the local actuated control for the traffic signal control. In this system, the green phase can be extended or truncated based on the flow rate of a platoon [25]. Stevanovic et al. presented an approach where a three-dimensional Pareto fronts of signal timing solutions are optimized by the use of an evolutionary algorithm in the stochastic optimization environment to bring a balance between mobility, safety, and environment [26].

Pescaru et al. proposed an integrated methodology for the adaptive traffic light control within a city zone. Their proposed method is based on an ensemble of classifiers that intelligently process the input data measured by a reduced number of sensors placed only on principal roads entering that zone [27]. Le et al. proposed a decentralized traffic signal control strategy based on the so-called *back pressure* policy for the urban road networks. Their approach does not require any apriori knowledge of the traffic demand and only needs the information that is local to the intersection [28].

Cong et al. considered a co-design approach with the aim of finding the optimal network topology and the optimal parameters of the traffic control laws simultaneously by solving a co-optimization problem [29]. Sun et al. developed a bi-level programming formulation and a Heuristic Solution Approach (HSA) for the dynamic traffic signal optimization in networks with time dependent demand and the stochastic route choice [30].

Li et al. proposed a self-adaptive traffic light control system which adjusts the traffic light signals in real time following the vehicles' speed messages in order to raise the passing capacity of the road [31]. Qi et al. used deterministic and stochastic Petri nets to design an emergency traffic light control system at an intersection dealing with accidents to ensure the safety of intersections and to prevent secondary injuries [32]. Cao et al. introduced a multi agent pheromone-based on a traffic management framework which aims to unify the vehicle rerouting and the traffic light control [33]. Fleck et al. applied and infinitesimal perturbation analysis based on a quasi-dynamic traffic light control for a single intersection which they modelled as a stochastic flow model [34].

3. Proposed Method

3. 1. Pedestrian Number Estimation

As there is a correlation between crowd density and texture patterns, texture features can be used to estimate pedestrian number in outdoor scenes. Jalali Moghaddam et al. proposed crowd density estimation method using texture descriptors based on Local Binary Pattern and Gabor filters [1]. A set of well-established 2-D Gabor filters are used to extract the global texture features, which can effectively solve the problems of overlap among crowd members and the perspective distortion.

3.1.1. Gabor Filters: A 2-D Gabor filter is a band-pass filter which is the product of a 2-D Gaussian kernel function with oriented sinusoids [36]. The Gabor filter can respond to the directed frequency components of different scaled textures. Thus, filtering can be performed at different scales to find patterns of different sizes. Moreover, applying multi-frequency and multi-direction Gabor filter significantly mitigates the issues of perspective distortion and occlusion. Therefore, the Gabor filter output can give effective texture descriptors for the pedestrian number estimation. In this paper, feature extraction in space and spatial-frequency domains can be done with even-symmetry (h_e) and odd-symmetry (h_o) Gabor filters via convolution as:

$$h_e(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \cos\left(2\pi\omega_0(x\cos\theta_0 + y\sin\theta_0)\right) \quad (1)$$

$$h_o(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \sin\left(2\pi\omega_0(x\cos\theta_0 + y\sin\theta_0)\right) \quad (2)$$

$$q_e(x,y) = p(x,y) \otimes h_e(x,y) \quad (3)$$

$$q_o(x,y) = p(x,y) \otimes h_o(x,y) \quad (4)$$

$$q(x,y) = \sqrt{{q_e}^2(x,y) + {q_o}^2(x,y)} \quad (5)$$

Where 〖 ω 〗 _0,θ_0,σ are the central frequency, orientation, and spatial constant, respectively, p is the input image and $\otimes$ denotes convolution. To diminish the sensitivity of this approach to monotonic illumination variations, Local Binary Pattern operator is applied.

3.1.2. Local Binary Pattern: Local Binary Pattern is one of the most powerful descriptors for texture analysis. Due to its tolerance to monotonic illumination changes and its computational simplicity, it has been widely used in many applications. LBP labels the pixels with the value obtained from its neighborhood pixels. Each neighbor in the 3×3 neighborhood of a pixel is compared with the pixel and is replaced with to 1 if it is larger than the pixel or 0 if it is smaller than the pixel. The corresponding decimal value of each pixel which is obtained by concatenating the binary values in a clockwise direction is then used for labeling the given pixel.

3.1.3. Pedestrian Number Estimation Method: After converting the input RGB images to gray level, we just use the sub-region of the image which is called the Region of Interest (ROI) to speed up the algorithm. The input image is enhanced with a 3×3 mean filter and histogram equalization. Next, the LBP algorithm is applied to reduce the monotonic gray-scale changes of the enhanced image. In the next step, the features are extracted from the LBP image using 24 two-dimensional visual cortical Gabor filters. Six values including 2, 4, 8, 16, 32, 64 are selected for frequencies (ω_0), four values consisting of 0°, 45°, 90° , and 135° are selected for orientations, and $\frac{1}{\omega_0}$ was selected for the spatial constant σ. Since the histograms of the channel output images are often close to a Gaussian shape [36], only the mean values and the standard deviations of channel output images are computed and used as texture features. Finally, we estimate the pedestrian number using the Least Square Support Vector Machine (LSSVM) regression toolbox [37] which is a reformulation to the standard SVMs which leads to solving linear KKT (Karush-Kuhn-Tucker) systems.

a. Vehicle Number Estimation

3.2.1. Gaussian Mixture Model (GMM): In the Gaussian Mixture Model, the value of a particular pixel is modelled by a mixture of k Gaussian distributions [38]:

$$p(x_t) = \sum_{i=1}^{k} \omega_{i.t} * \eta(x_t, \mu_{i,t}, \Sigma_{i,t}) \quad (6)$$

where k is number of distributions, and $\omega_{i,t}$, $\mu_{i,t}$, and $\Sigma_{i,t}$ are the weight, the mean, and the covariance of the i^th Gaussian at time t, respectively. In addition, η is a Gaussian probability density function [38].

The Gaussians are ordered by the value of ω/σ. The B first distributions are selected as the background model. A match is defined as a pixel value within 2.5 standard deviations of a distribution.

A current pixel value that does not match any of the k distributions with sufficient supporting evidence is labelled as foreground. In case of the mismatch, the least probable component is replaced with a new distribution whose mean value is set to the new pixel value and its variance and prior weight are initialized to a high and a low value, respectively. If a distribution is matched with the new observation, the parameters of the distribution are updated as:

$$\mu_t = (1\text{-}\rho)\, \mu_{t-1} + \rho\, x_t \quad (7)$$

$$\sigma_t^2 = (1\text{-}\rho)\, \sigma_{t-1}^2 + \rho (x_t - \mu_t)^T (x_t - \mu_t) \quad (8)$$

$$\rho = \alpha\, \eta(x_t / \mu_k, \sigma_k) \quad (9)$$

This approach does not need any prior environmental knowledge and can deal with slow lighting changes by slowly adapting the values of the Gaussians.

3.2.2. Vehicle Number Estimation Method: The RGB input images are first converted to gray level images and a ROI-based method was used for vehicle detection to speed up the algorithm. Then, a GMM background subtraction method was applied to segment the moving regions in the current frame. The segmented region is called as the foreground mask. After segmentation, the foreground mask was enhanced with a 3×3 median filter. Next, adaptive blocking was used to mitigate the issues of perspective distortion. In this stage, a multi-scale patch size is used. The ratio of the number of foreground pixels to the number of background pixels in each block was calculated and considered as a training feature vector. Finally, the vehicle number was estimated using the Least Square Support Vector Machine (LSSVM) regression.

3.3. Traffic Light Control

The proposed method for traffic light control is shown in Fig. 1. Q-learning has been used for learning in fuzzy systems [39]. Since the state and actions of Q-learning algorithm can be set by fuzzy variables, Q-learning can take advantage of fuzziness. A Fuzzy Q-learning controller and a fuzzy controller are designed for the traffic light and the pedestrian traffic light controls, respectively, for an isolated 4-way traffic intersection. The Q-learning information is used in tuning the output membership functions of the fuzzy controller. The Fuzzy Q-learning and fuzzy controllers can operate based on linguistic rules like humans similar to the policeman handling the traffic flow at a junction.

In this paper, Fuzzy Q-learning traffic light control is introduced according to vehicle density and pedestrian number estimated using visual information to minimize the waiting time and maximize the throughput of the intersection. The green light and the red light specified the arrival side and queue side, respectively. If the north and south side is green then this would be considered as the arrival side, while the west and east side would be considered as the queuing side, and vice-versa. Three input variables are considered for the traffic lights control:

- Max_ql_ns: the maximum number of vehicles in the north-south and the south-north (max (ql_north, ql_south))
- Max_ql_ew: the maximum number of vehicles in the east-west and west-east (max (ql_east, ql_west))
- Ped_num: the maximum number of pedestrian waiting in the arrival side (max (p_ar_1, p_ar_2))

The fuzzy variable determined the optimal traffic light duration for the arrival side. Before the end of each phase, the next green optimum phase durations being estimated based on the current traffic conditions are specified by four variables including the number of vehicles in the north (ql_north), the south (ql_south), the east (ql_east), and the west (ql_west). The proposed algorithm determined the optimal next phase duration for the queue side based on the current queue lengths. The north-south and east-west Q-tables are used where the size is determined as:

$$Q_{table} - size = noas * noqs * NOaction \qquad (10)$$

where noas is the number of the arrival side membership functions, noqs is the number of the queue side membership functions, and NOaction is the number of actions.

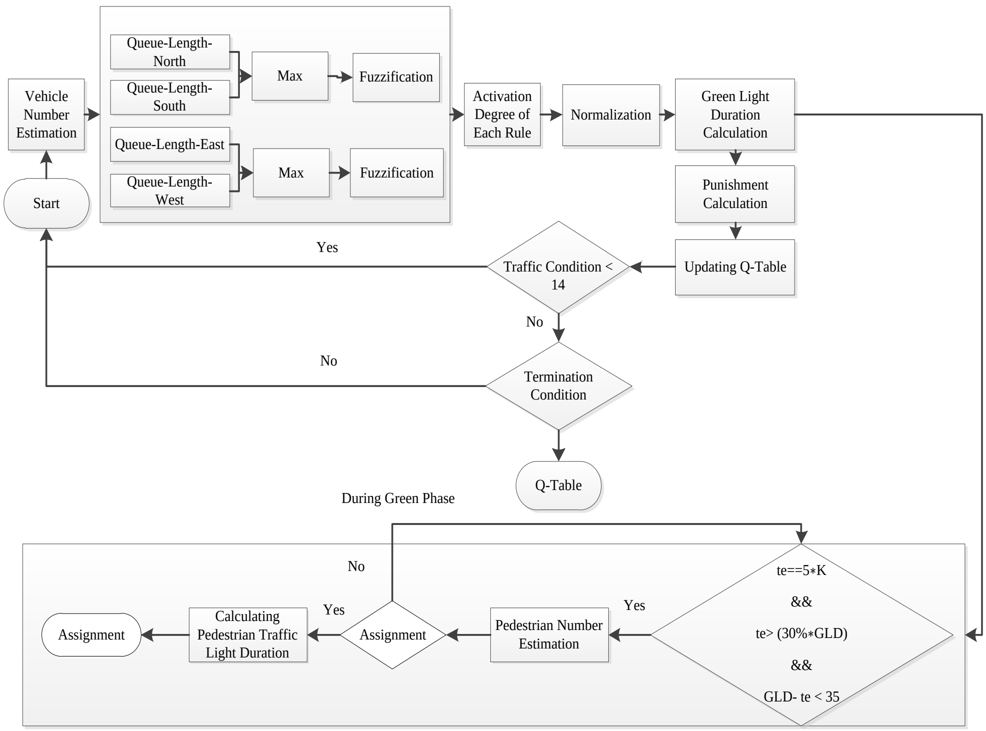

Fig. 1. Fuzzy Q-Learning Traffic Light Control Schematic

The proposed algorithm is described as follows:

1. Based on the number of vehicles in each queue, the variables Max_ql_ns and Max_ql_ew are calculated as an input for the next step of the algorithm.
2. Four fuzzy sets are defined on each dimension of the two dimensional state space, mf_{ns}^{i} and mf_{ew}^{i} are the corresponding membership function in which i ϵ {low, medium, high, very high} as are illustrated in Fig. 2. Each rule is associated with a set of possible discrete actions $Act_{j_1,j_2} = \{act_{j_1,j_2,r_1}, act_{j_1,j_2,r_2}, \ldots, act_{j_1,j_2,r_k}\}$ where j_1, j_2= 1, 2 ,… , show the number of membership functions, and r = 1, 2, …, n_R where n_R is the number of rules. The corresponding action values are defined as follow:

$$Q_{j_1,j_2} = \{q_{j_1,j_2,r_1}, q_{j_1,j_2,r_2}, \ldots, q_{j_1,j_2,r_k}\} \tag{11}$$

According to the above definitions, the generic rule R_r may be written as:

R_r : If Max_ql_ns is mf_{ns}^{i} and Max_ql_ew is mf_{ew}^{i}
Then output = $a_{r,1}$ with $q_{r,1}$
OR
.
.
.
OR
output = a_{r,n_R} with q_{r,n_R}

When Max_ql_ns and Max_ql_ew enter the system, they are fuzzified based on the membership function. All of the rules are activated partially by a certain activation level which is calculated as:

$$\varphi_r = \mu_{ns}^{i}(Max\_ql\_ns) * \mu_{ew}^{i}(Max\_ql\_ew) \tag{12}$$

where μ_{ns} and μ_{ew} are truth degrees.

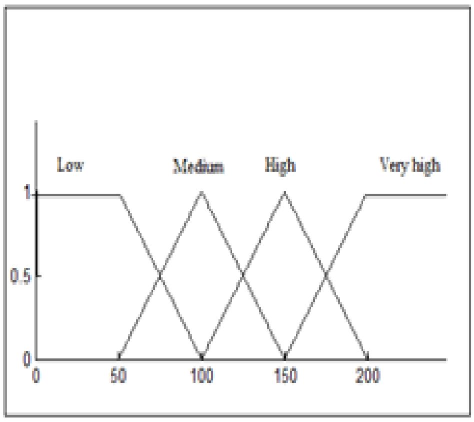

Fig. 2. The membership functions for arrival side and queue side

3. Since each input variable belongs to several fuzzy sets with different activation levels, the activation level is normalized and is considered as the weight of each of the winning actions of the rule:

$$\varphi\_norm_r = \frac{\varphi_r}{\sum_{r=1}^{N_r}\varphi_r} \tag{13}$$

4. The time of the green light is calculated based on the average weight method:

$$Act = \sum_{r=1}^{N_r}\varphi_r * win\_act_r \tag{14}$$

where φ_r and win_act_r are the weight and wining action of the r^th rule, respectively.

5. After the calculation of the next green light duration, the output value which is between -1 and 1, is mapped to the original range. In this paper, the original range is multiples of 5 between 10 and 100.
6. After each phase, the punishment is calculated based on the queue length variation as:

$$Punishment = \sum_{i=1}^{4}(log(max(|ql_i^{new} - ql_i^{old}|),1) * sgn(ql_i^{new} - ql_i^{old})) \tag{15}$$

where $ql_i \in \{ql_{north}, ql_{south}, ql_{east}, ql_{west}\}$

7. The arrival side Q table is updated after calculating the punishment. Gradient descent is usually used to update the parameters of the algorithm:

$$\begin{aligned} q_{r,i}^{t+1} &= q_{r,i}^{t} - \alpha\varepsilon_Q^t\psi_r \\ \varepsilon_Q^t &= Punishment - (\gamma \max_a Q(s^{t+1},a) \\ &\quad - Q^t\left(s^t, A^t(x^t)\right)) \\ \max_a Q(s^{t+1},a) &= \sum_{r=1}^{n_R}\psi_r \max_i \{q_{r,i}^t\} \end{aligned} \tag{16}$$

where γ is the discount factor and α is the learning rate.

8. The above steps are done for each of the 14 different traffic conditions in one hour simulations and then are repeated until the convergence has emerged.
9. Assume t_e shows the elapsed time of the green phase and GLD is the duration of the current green traffic light. At the test time, during each green phase, in the time interval that t_e is greater than 30%*t_{GLD} and the reminder time of the green light is more than 35 seconds. The pedestrian traffic light estimation procedure is run to make a decision for the allocation or not allocation of the pedestrian traffic light. In case of allocation, the pedestrian traffic light duration is specified based on fuzzy rules that are shown in Table 1 and the pedestrian membership function shown in Fig. 3. In this procedure, the pedestrian number is estimated based on algorithm 2.1. every 5 seconds, and the decision making for the pedestrian traffic light is done based on a fuzzy controller system.

A total of 9 fuzzy rules were established to construct the fuzzy controller. These rules are set based on the required time for the pedestrian passing which is related to the street's width and the pedestrians' group speed in group that are extracted from traffic video images in different times and streets. The elapsed time and the pedestrian green light duration values are shown with t_e and t_p, respectively. During the green phase of the pedestrian traffic light, the traffic light for the queue side and the arrival side switch to green and red, respectively.

10. At the end of the green phase of the pedestrian traffic light, the arrival side traffic light changes to green again. As

t_p seconds of the green phase were allocated to pedestrian traffic light, the reminder of the green duration is calculated based on the pedestrian green phase duration and elapsed time and is reallocated to the arrival side. This value can be obtained as follow:

$$t_r = GLD - (t_e + t_p) \tag{17}$$

11. The above steps are done for each of the 14 different traffic conditions in one hour simulations.

Table 1 Fuzzy rules for pedestrian traffic light control

Pedestrian Density	Arrival Side	Green Phase Duration
Low	Low	No Allocation
Low	Medium	No Allocation
Low	High	No Allocation
Medium	Low	Medium
Medium	Medium	Medium
Medium	High	Low
High	Low	High
High	Medium	Medium
High	High	Low

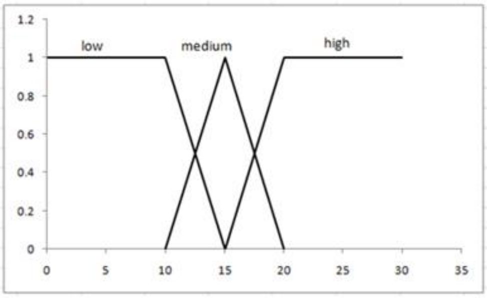

Fig. 3. The pedestrian membership

4. Experiments

a. Experimental Setting

The proposed approach for crowd density estimation is evaluated within the collected video image dataset by the Tehran Transportation and Traffic Organization (TTTO). We manually selected images to cover all vehicle and pedestrian congestion levels, brightness levels and shadows. Based on the manual estimation, the images were labelled. To use all data for both training and testing, we have used a 10-fold cross validation. We randomly broke data into 10 sets. In order to evaluate the proposed algorithms to estimate the vehicle number, the parameter values were set to k=3, T=0.33, and α=0.05.

The proposed algorithm for traffic light control is simulated for one hour for each of the 14 traffic conditions that are presented in table 2 [40]. Vehicle arrival and departure rates are simulated using Poisson distributions on each street as shown in table 2. In order to evaluate the proposed algorithm, the parameter values are set as: γ =0.8, ε=0.01, and α =0.2. After each 14 states, alpha is updated with a 0.99 update rate. In each phase, based on the ε-greedy exploration strategy, the best action with probability $1 - \varepsilon$ and a random action with probability ε is selected for each rule. The departure rates for all conditions are set equal to 1. Pedestrian arrival and departure rates are simulated using Poisson distributions on each street based on the mean rates obtained based on the video image dataset which is captured by the TTTO. These algorithms are implemented using Matlab on an Intel® core i5 M460 2.53 GHz PC with 4 GB RAM.

b. Experimental Results

In this section, we present the results of our experiments. The pedestrian and vehicle number estimation algorithms are assessed on Tehran traffic video dataset collected by transportation and traffic organization. The ground-truth count and the number calculated by algorithm are compared by the Mean Absolute Error (MAE) measurement:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} C(i) - T(i) \tag{18}$$

where N is the number of frames of the test sequence and C(i) and T(i) are the calculated and the ground-truth number of pedestrians and vehicles in the i^{th} frame, respectively.

We also compared the proposed traffic light control algorithm with two other traffic light control methods, namely PCT and VA on the 14 traffic conditions. Based on the arrival and departure time of each vehicle, the total waiting time and the mean queue length are calculated. The Mean of Total Waiting time (MTW) and the Mean of Queue Lengths (MQL) are calculated for each algorithm in table 3. According to this table, the mean of the queue length and the mean of total waiting time of the results are nearly similar in the light, and the moderate traffic condition which are coloured in black. The important case appears in the heavy traffic conditions. Our algorithm achieves a better result than the other algorithms, especially in the unbalanced traffic conditions, where the input rate of one side is heavy and other methods show critical results. The mean total waiting time of the three algorithms are compared in Fig. 4. PCT and VA face difficulties in the more unbalanced condition and heavier input rate. However the proposed algorithm can deal with such conditions and achieve better results. The comparison of the mean of queue length of the three algorithms is illustrated in Fig. 5. In asymmetrical traffic increase from different directions, the proposed system can control traffic in shorter mean queue length and total waiting time.

In the last part of the experiment, we assessed the proposed algorithm for the traffic light control in 14 traffic conditions. The pedestrian arrival and the departure rates are simulated using Poisson distributions on each street based on the mean rates obtained from the video image dataset in different traffic, time, and illumination conditions which is captured by the transport and traffic organization. This part of the experiment is considered to assess the proposed pedestrian traffic light control system. The mean waiting time of pedestrians is shown in Fig. 6. This time is evaluated based on the difference between each pedestrian's arrival time and the starting time of the next green phase of the pedestrian traffic light.

If a pedestrian arrives in the green phase of the pedestrian traffic light, this time is equal to zero. As shown in Table 4, the proposed approach could decrease the pedestrian waiting time significantly.

Table 4 The mean of total waiting, mean of queue length, and mean of total pedestrian waiting of fuzzy proposed algorithm

Traffic Condition	Algorithm					
	Proposed Approach Without Pedestrian Traffic Light			Proposed Approach With Pedestrian Traffic Light		
	MQL	MTW	MTPW	MQL	MTW	MTPW
1	1.71	7.81	9.46	1.75	7.93	9.46
2	29.81	69.5	34.12	36.31	77.05	22.45
3	293.84	496.27	59.32	313.18	480.41	30.31
4	34.24	71.71	26.16	36.68	71.43	20.68
5	28.54	60.14	26.4	36.66	56.35	20.67
6	21.34	45.17	25.44	34.4	38.31	20.62
7	21.78	47.31	28.06	35.23	44.01	20.96
8	27.85	66.66	42.54	30.32	63.61	25.19
9	29.30	77.77	42.92	30.11	65.59	25.32
10	24.03	49.67	43	27.03	48.14	25.37
11	33.19	86.47	42.92	37.09	80.93	25.22
12	1.29	7.05	17.29	1.38	7.41	16.78
13	229.71	367.58	56.58	244.52	352.68	29.44
14	38.84	74.85	44.81	47.27	78.14	26.44

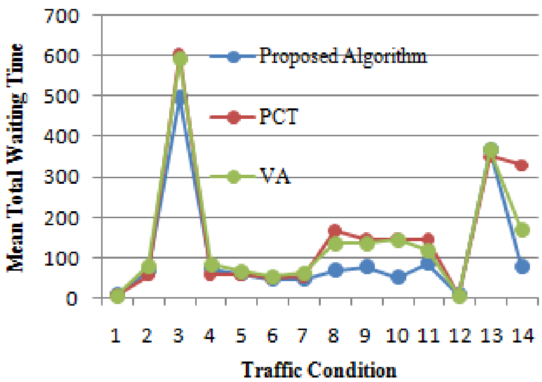

Fig. 4. The mean total waiting time

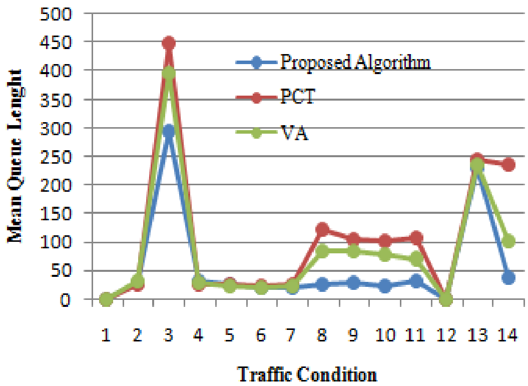

Fig. 5. The mean of queue length

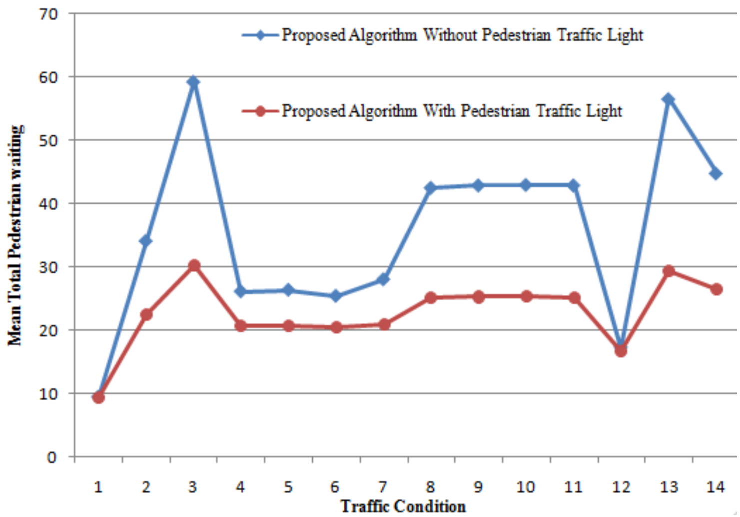

Fig. 6. The mean pedestrian waiting time

Table 2. Intersection traffic conditions [40]

Traffic condition	state	Input rate				description
		North	south	east	west	
balanced	1	0.25	0.25	0.25	0.25	Light traffic
	2	0.5	0.5	0.5	0.5	Moderate traffic
	3	0.75	0.75	0.75	0.75	Heavy traffic
Unbalanced	4	0.25	0.5	0.5	0.5	North has light traffic and south, east and west have moderate traffic
	5	0.5	0.25	0.25	0.25	North has moderate traffic and south, east and west have light traffic
	6	0.5	0.5	0.25	0.5	East has light traffic and north, south and west have moderate traffic
	7	0.5	0.5	0.5	0.25	west has light traffic and north, south and east have moderate traffic
	8	0.75	0.25	0.25	0.25	North has heavy traffic and south, east and west have light traffic
	9	0.25	0.75	0.25	0.25	South has heavy traffic and north, east and west have light traffic
	10	0.25	0.25	0.75	0.25	east has heavy traffic and north, south and west have light traffic
	11	0.25	0.25	0.25	0.75	west has heavy traffic and north, south and east have light traffic
complementary	12	0.25	0.5	0.25	0.5	North and east have light traffic and south and west have moderate traffic
	13	0.75	0.5	0.75	0.5	North and east have heavy traffic and south and west have moderate traffic
	14	0.25	0.75	0.25	0.75	North and east have light traffic and south and west have heavy traffic

Table 3. The mean of total waiting and mean of queue length of diffrent algorithms.

Traffic Condition	Algorithm					
	Proposed Approach		PCT		VA	
	MQL	MTW	MQL	MTW	MQL	MTW
1	1.71	7.81	1.8	6.74	1.46	5.49
2	29.81	69.5	26.53	55.05	34.28	78.72
3	293.84	496.27	447.85	603.52	397.09	592.21
4	34.24	71.71	28.01	57.56	29.91	84.06
5	28.54	60.14	27.75	57.64	24.08	64.45
6	21.34	45.17	22.91	47.03	22.42	51.97
7	21.78	47.31	26.7	54.64	25.62	63.46
8	27.85	66.66	121.67	164.6	84.22	135.28
9	29.30	77.77	105.07	145.61	85.16	136.3
10	24.03	49.67	103.36	145.82	81.07	143.28
11	33.19	86.47	107.43	145.69	72.42	117.97
12	1.29	7.05	1.09	5.26	1.1	5.43
13	229.71	367.58	246.06	349.97	237.38	367.6
14	38.84	74.85	236.6	328.79	102.59	168.06

5. Conclusions

Traffic is an issue that many big cities are confronted with because of the ever-increasing population. In this paper, we proposed a two phase traffic light control system based on fuzzy Q-learning for an isolated 4-way intersection. A fuzzy algorithm sets the Q-learning variables. The proposed algorithm benefits from fuzzy system advantages and can learn fuzzy rules using environmental interactions. Before the end of each phase, the next green optimum phase durations estimated based on the current traffic conditions are specified. The proposed system operates based on the detection of pedestrians and vehicles in video frames captured by cameras installed on the intersection and then perform accurate counting of pedestrians and vehicles. A pedestrian number estimation method is employed to find a mathematical relationship between the global texture features of a crowded scene and the number of people in the scene. Also, the vehicle number estimation algorithm is proposed to determine the traffic density using visual information. A dynamic background subtraction technique for vehicle detection has been used to achieve better detection efficiency. This algorithm was compared with two other algorithms, namely VA and PCT, for a period of one hour for each of 14 different traffic conditions. As shown in the results, the proposed algorithm surpassed the other algorithms both in term of waiting time and queue length significantly in heavy traffic and unbalanced traffic conditions, whereas in other situations the three algorithms were similar.

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