Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 109C (2017) 1182–1187

Procedia Computer Science

www.elsevier.com/locate/procedia

International Workshop on Adaptive Technology
(WAT 2017)

Adaptive traffic signal control based on bio-neural network

Guilherme B. Castro[a], André R. Hirakawa[a], José S. C. Martini[a]*

[a]*Politecnica School-University of São Paulo, Av. Prof. Luciano Gualberto, t3, 158, São Paulo-05508-900, Brazil*

Abstract

Urban traffic management is one of the major concerns for big cities around the world, due to its negative impacts on society. Several approaches of traffic signal control based on artificial intelligence techniques or on control theory were proposed as alternatives to mitigate this problem. However, it is a challenge to reach a good solution, as the urban traffic is a complex and dynamic ecosystem. On this scenario, this paper proposes an adaptive biologically-inspired neural network that receives the system state and is able to change the behavior of the control scheme as well as the order of semaphore phases, instead of prefixed cycle-based ones. Proposed adaptive control was evaluated on a single intersection scenario. Despite analyzing the control of a single intersection, the model proposed is modular, allowing the control of multiple intersections. The analyses conducted herein showed that the model is robust to different initial conditions and has fast adaptation between system equilibrium states. Simulations with SUMO showed a better performance than a cycle-based traffic responsive control method regarding reactivity and capacity tests, in which the relevance of the constant monitoring and acting became evident.

Peer-review under responsibility of the Conference Program Chairs.

Keywords: Biologically-inspired neural network, complex dynamic systems, traffic signal control.

1. Introduction

The increase of traffic volume causes even more traffic jam due to the slow-paced and, the non-existent improvements in the urban traffic infrastructure. Traffic jam is a direct result of higher vehicle traffic over the city capacity and also unpredictive events like traffic accidents and climate effects. Healey and Picard[1] analyzed the

* Corresponding author. Tel.: +55-11-3091-5271; fax: +55-11-3091-5294.
E-mail address: andre.hirakawa@poli.usp.br

Peer-review under responsibility of the Conference Program Chairs.
10.1016/j.procs.2017.05.394

impacts of urban traffic on human health, showing increased stress in situations of traffic jam. Furthermore, Grillo and Laperrouze[2] discussed the effects of traffic jam on the Gross Domestic Product (GDP) and on the environment, attributing its main causes to the cost of fuel, the opportunity cost of the time citizens spend in traffic, and CO2 emission. Traffic signal control is a cost-efficient alternative to improve the system efficiency, i.e., to increase the city capacity with the same urban infrastructure. Optimized vehicle flows reduce vehicle stops at traffic signals as well as their average travel times, preventing traffic jams. Different approaches have been proposed to control the traffic signals of urban networks, like ones based on the optimal control theory and on artificial intelligence techniques. However, it is challenging to find out a good solution for traffic signal control, because of the intrinsic complexity of the system. The urban traffic is dynamic and has uncertain nature, interdependent subsystems, nonlinearities, and great amount of variables, such as vehicle flows, vehicle queues and semaphore phase times.

On this context, Castro[3] investigated a model for traffic signal control based on the positive results of biologically-inspired neural networks for the control of complex systems, presenting its mathematical formalism, analyzing its behavior as well as the complex dynamic system, and evaluating its control performance. In contrast to other approaches, the proposed model does not have a prefixed order of semaphore phases, and thus is able to change control behavior in accordance to urban traffic state.

2. Related works

Initial solutions for traffic signal control were based on optimization methods that uses fixed green times for semaphores in order to reduce the average travel time of vehicles. As the urban traffic is a dynamic environment, adaptive approaches were then proposed to further decrease average travel time, readjusting semaphore green times during their operation. These control methods are also called vehicle actuated or traffic responsive, among which the most applied are LHOVRA[4] and others. However, they have a centralized structure, having restricted control efficiencies due to the long time required to exchange information of all intersections and to make a global decision.

Timotheou[5] et al. adopted linearized macroscopic models of the urban traffic as a basis for model predictive control (MPC) methods that focused on the distribution of the prediction and control capacities. Zhao[6] et al. stated that the use of macroscopic models to simplify urban traffic control limits its control efficiency, disregarding the complete dynamics of vehicles and semaphores. In addition, Gokulan and Srinivasan[7] claim that macroscopic urban traffic models that consider system uncertainties or try to predict its behavior are inaccurate and computational intensive. Regarding artificial intelligence techniques, Srinivasan[8] et al. proposed an artificial neural network for traffic signal control. The main advantage of control methods based on learning is that they do not require a model of the system. However, according to Gokulan and Srinivasan[7] these methods demand an infeasible amount of data and training time to adequately represent the behavior of stochastic systems with many variables, such as the urban traffic. A common disadvantage of the aforementioned control methods is that they are cycle-based, i.e., they only adjust semaphore green times after each cycle, which limits the system reactivity and, thus, its efficiency. Hamilton[9] et al. proposed a more flexible approach, which is based on a linear model but does not establish a fixed phase order or cycle length and is able to change semaphore phases at any moment, obtaining an increase in control performance in comparison to a cycle-based control method.

On the other hand, biologically-inspired neural networks differ from artificial neural networks as it explores more biological characteristics of real neurons in order to improve the overall dynamic behavior of the model, whereas one that focuses on the learning aspect of neural networks. Thereby, biologically-inspired neural networks do not usually have a training stage, choosing instead their synaptic weights to achieve a desired behavior. A variety of biologically-inspired neural networks were proposed for controlling dynamic systems, mainly in robotics. Robot control is similar to the control of complex dynamic systems, such as the urban traffic, because of the number of variables, nonlinearities, and environment uncertainties involved. Besides the unique structure of each neural network, these works adopt different types of neuron models, synapses and long and short term plasticity. Nichols[10] et al. proposed a pulsating neural network for robot control and adopted the leaky-integrator neuron model due to its low computational cost. Castro[3] et al. proposed a biologically-inspired neural network for traffic signal control and validated it with comparative simulations. The proposed neural network adopts the same neuron model adopted by Yang[10] et al. which represents the behavior of real neurons with low computational cost and is conventionally present in artificial neural networks. The proposed model has an adaptation mechanism, or short term plasticity. The proposed neural network has excitatory and inhibitory neurons and is more realistic concerning biological neurons.

3. Adaptive bio-neural network

The scenario studied comprises a single intersection with four semaphore phases, shown in Fig. 1 along with the enabled vehicle flows of each phase. This intersection is more complex in terms of control because a part of the flows is enabled in more than one phase. The proposed bio-neural network is shown in Fig. 2. In the proposed model, each semaphore phase is represented by an excitatory neuron with intrinsic plasticity, which is the adaptation mechanism of the model. In the figure, sensorial receptors q_a to q_f represent the vehicle queues of lanes *a* to *f*, which are inputs of the system. Inputs q_a to q_f change in accordance to dynamic traffic behavior and induces two kinds of adaptation process into the bio-neural network. First type of adaptation is related to normal operation of the intersection when traffic in each lane is well balanced, which means q_a to q_f with similar value. In these conditions, the adaptation process tries to optimize the time of each semaphore phase. Second type of adaptation is related to the occurrence of any event when inputs q_a to q_f present severe unbalancement. In this situation, the adaptation mechanism can change the time of each phase or even suppress one of them. All of adaptation process is accomplished by the intrinsic plasticity that facilitates the transition between active neurons by progressively increasing the activation of inactive neurons and decreasing the activation of active neurons. The output produced by neuron activates the corresponding semaphore phase, enabling its vehicle flows with green lights. For simplicity, the yellow period of the traffic lights was excluded and considered as in the red period. According to Gokulan and Srinivasan[7], the use of vehicle queues or lane occupations as system inputs is suitable, because they reflect the vehicle delay to cross the controlled intersection. Gerolimini and Skabardonis[11] and Zhang[12] reinforce this choice, demonstrating the decrease of the urban traffic system efficiency when a street saturates and causes the spillover effect. As the inputs of an intersection are the outputs of its immediate neighbors, weak couplings between neighboring intersections are established, does not requiring communication between intersections.

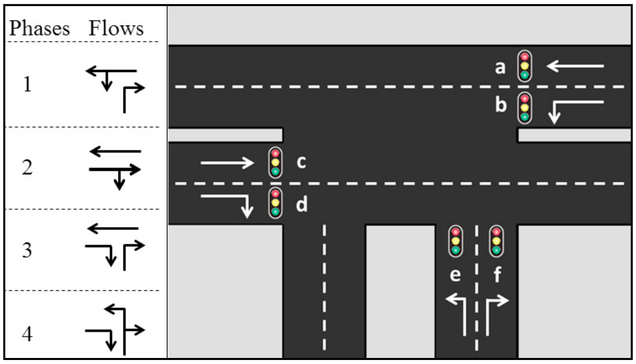

Fig. 1. Intersection model and semaphore phases.

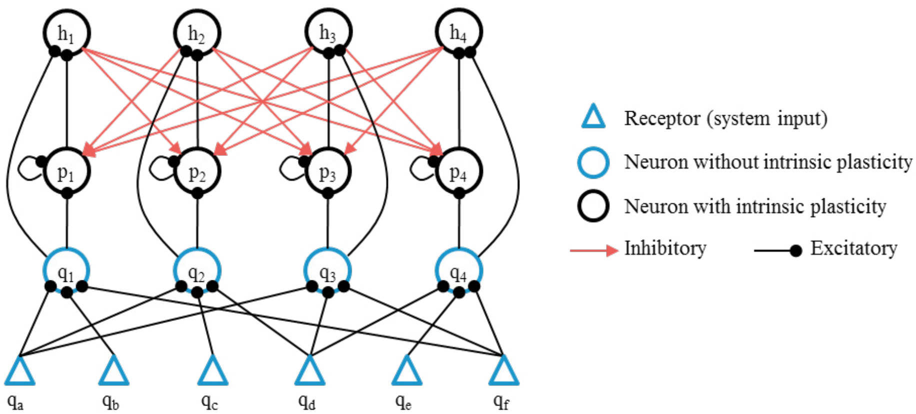

Fig. 2. Structure of the biologically-inspired neural network.

In the proposed model, neurons *q1* to *q4* aggregate the inputs of each phase and do not have intrinsic plasticity, as biological bipolar neurons (Kandel[13] et al.). Neurons *p1* to *p4* represent the phases of the semaphores, whereas neurons *h1* to *h4* represent their respective inhibitory neurons, which inhibit other phases activity with lateral inhibition dynamics. The model includes two types of inhibition: feed forward, which connects system inputs directly to inhibitory neurons, anticipating input changes and facilitating neuron state transition; and feedback, which reflects the current state of *p* neurons and maintains its activation by inhibiting the other p neurons. Thereby, synapses between *q* and *h* neurons originate feed forward inhibition, whereas synapses between *p* and *h* neurons originate feedback inhibition. Recurrent synapses of *p* neurons reinforce their activation, representing the effect of biological G-Proteins.

The equations that govern the proposed neural network are based on the principles stated by Peláez and Andina[14] whose general form is given by (1), (2), (3) and (4). Equation (1) determines the activation of phase neurons, whereas (2) determines the activation of inhibitory neurons. Equation (3) determines the shift of the activation function of neurons, which is responsible for the adaptation mechanism of the model, whilst (4) determines the neuron output.

$$A_{p,i}^{t+1} = \sum_{j\in N_i} w_q I_j^t + w_p O_{p,i}^t - \sum_{k\in M_i} w_h O_{h,k}^t \quad (1)$$

$$A_{h,i}^{t+1} = \sum_{j\in N_i} w_{qh} I_j^t + w_{ph} O_{p,i}^t \quad (2)$$

$$s_i^{t+1} = \frac{\xi O_i^t + s_i^t}{\xi + 1} \quad (3)$$

$$O_i^t = \frac{1}{1+e^{-\alpha\left(A_i^t - s_i^t\right)}} \quad (4)$$

In the equations, $A_{p,i}$ is the activation of phase neurons, whereas $A_{h,i}$ is the activation of inhibitory neurons. Concerning the synaptic weights, w_q is the synapses between inputs and phase neurons, w_p to recurrent synapses of phase neurons, w_h to synapses between inhibitory neurons and phase neurons, w_{qh} to synapses between inputs and inhibitory neurons, and w_{ph} to synapses between phase neurons and inhibitory neurons. N_i is the set of system inputs I_j (queues of vehicles) of phase neuron *i*, whose output is denoted by $O_{p,i}$. M_i is the set of inhibitory inputs $O_{h,k}$ of phase neuron *i,* which are also the outputs of the inhibitory neurons. In (3), s_i is the shift of the activation function of neuron *i*, whereas O_i is its output and ξ is the shifting-rate of the activation function. In (4), O_i is the output of neuron *i*, A_i is its activation, s_i is the shift of its activation function and α is the slope of the activation function. The system inputs I_j are restricted by $0 < I_j^t < 1$ and s_i, is also restricted by $0 < I_j^t < 1$

4. Evaluation of the proposal

The proposed biologically-inspired neural network was implemented in MATLAB to evaluate its performance concerning its adaptation on traffic change. The scenario was modeled in a simulator of urban mobility, SUMO, and the software interface was accomplished by the protocol TraCI4Matlab (Gil[15] et al.). All the simulation vehicles have the same size, according to the passenger car equivalent (PCE) assumption (Keller and Saklas[165]), and a stochastic driving behavior (sigma equals 0.5).

In the simulations, the biologically-inspired neural network was compared to a well known traffic responsive control method, which adopts fixed cycles of two minutes and distributes the phase green times according to the number of vehicles in each lane, i.e., the same system inputs as the biologically-inspired neural network. The neural network parameters adopted for the simulations were: shifting-rate of the activation function ξ equal to 0.07; synaptic weight *wq* equal to 1, whereas *wp* and *wqh* equal to 0.4, and *wh* and *wph* equal to 0.3.

As a dynamic system, the urban traffic is subject to sudden variations in traffic volume and distribution. In this study, the control methods reactivity is evaluated with their responses to a pulse of vehicle demand. Fig. 3 shows this pulse, which corresponds to a 95.2% increase in the vehicle demand for 5 minutes, as well as the points in which the control methods measure the system state and act accordingly. The traffic responsive (TR) control method has two control cycle configurations, 2 and 10 minutes, whereas the sampling of the biologically-inspired neural network (BiNN) is so frequent that the points resemble a continuous line. Fig. 4 and 5 show the control methods responses to the pulse input.

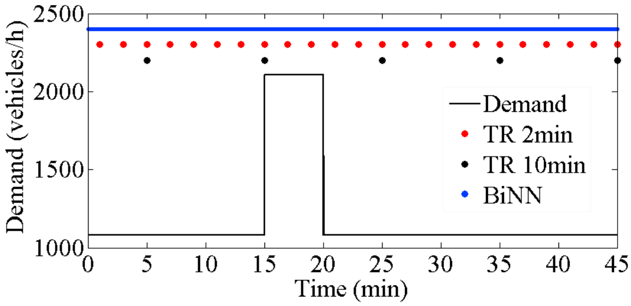

Fig. 3. Pulse of vehicle demand for adaptation evaluation.

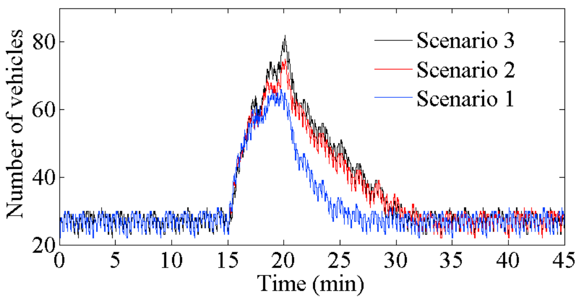

Fig. 4. Simulation results of the traffic responsive control method.

Fig. 4 shows three different scenarios of the traffic responsive control method: (Scenario 1) a pulse of equal vehicle demand in all lanes, i.e. just an increase of traffic volume; (Scenario 2) a pulse of vehicle demand in only one street of the intersection, causing a change in the demand distribution; (Scenario 3) the same pulse of the second scenario, but with a control cycle of 10 minutes, instead of 2 minutes. In spite of having the same vehicle demand, the second and third scenarios present performances respectively 133% and 161% worse than the first scenario in terms of maximum vehicle queue. In the first scenario, which has only a demand increase, the responsive control method does not need to adjust the green times distribution, showing a performance comparable to the biologically-inspired neural network. However, the second and third scenarios show that control cycles of 2 and 10 minutes are not small enough to react to a 5 minutes pulse of traffic redistribution, causing the observed decrease in control performance.

Concerning the biologically-inspired neural network, the results of two simulation scenarios are presented in Fig. 5. In the Scenario 1, the demand pulse has equal demand distribution, whereas in the Scenario 2 the additional vehicle demand regards only one street of the intersection. The results show an increase of 38% in the maximum vehicle queue of the second scenario in comparison to the first one, due to the concentration of demand in only one street. Nevertheless, the maximum number of vehicles at the intersection remains the same in both scenarios and is better than the responsive control. Another evaluation criterion is the capacity of control vehicle demand they without saturating. The number of vehicles in the controlled intersection is measured under different vehicle flow rates in three-hour simulations. Fig. 6 shows the simulation results, in which the red lines represent the performance of the traffic responsive control method and the blue lines represent the performance of the biologically-inspired neural network. Each line corresponds to a simulation run with constant vehicle flow rate, whose value is displayed on the right-hand side of the figure. The maximum number of vehicles at this intersection is 630.

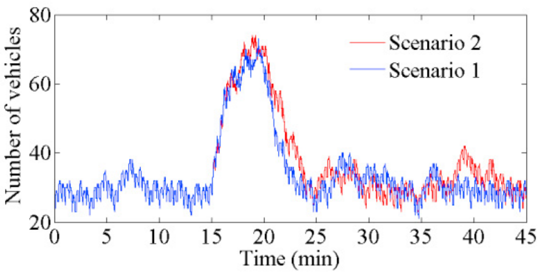

Fig. 5. Simulation results of the biologically-inspired neural network.

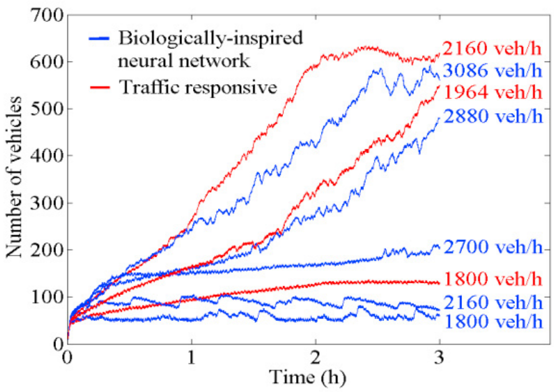

Fig. 6. Simulation results of control response.

The results in Fig. 6 show that, for equal vehicle flow rates, the performance of the biologically-inspired neural network is better in all cases. This is due to two main aspects of the model proposed: its adaptability and reactivity. The graphics slopes indicate the speed at which the vehicles accumulate into queues, and correspond to the difference between the control methods adaptability and the current vehicle demand. The traffic responsive control method is still able to withstand a demand of 1964 vehicles per hour for three hours without saturating, regardless of the vehicle demand being 9.1% higher than the method. On the other hand, the biologically-inspired neural network does not saturate under a demand of 3086 vehicles per hour for three hours, which is 14.3% higher.

5. Conclusion

This paper proposed an adaptive traffic signal control based on a biologically-inspired neural network applied to the scenario of urban complex and dynamic system.

The model used allows implementing adaptive control scheme that can change each semaphore cycle time, as well as, change in the sequence of cycles.

The performance evaluation attested that the proposed model has higher adaptability and capacity than the previous traffic responsive control method, which is mainly attributed to its flexible and constant system monitoring and acting possibility. Thereby, the proposed model overcame the aliasing effect, which deteriorates the performance of cycle-based control methods.

Future research includes stability analysis with the system eigenvalues and, thus, the extension of the model mathematical formalism to determine its parameters according to the desired behavior. Thereafter, the emergent system behavior of the control of multiple intersections will be investigated considering green wave formation and spillover prevention, and the model auto-organization and fault tolerance will be evaluated.

References

1. Healey, J. A., Picard, R. W., Detecting stress during real-world driving tasks using physiological sensors. *IEEE Trans. Intell. Transp. Syst.* 6(2), 156-166, 2005.
2. Grillo, F., Laperrouze, J., Measuring the cost of congestion on urban area and the flexible congestion rights. *Journal of Management and Sustainability* 3(2), 40-55, 2013.
3. Castro, G. B., Martini, J. S. C., Hirakawa, A. R., Biologically-inspired neural network for traffic signal control. *17th IEEE ITSC*, pp. 2144-2149, 2014.
4. Peterson, A., Bergh, T., Steen, K., LHOVRA, a new traffic signal control strategy for isolated junctions. *In: Proc. 2nd International Conference on Road Traffic Control*, pp. 98-101, 1986.
5. Timotheou, S., Panayiotou, C. G., Polycarpou, M. M., Distributed traffic signal control using the cell transmission model via the alternating direction method of multipliers. *IEEE Trans. Intell. Transp. Syst.* 16(2), 919-933, 2015.
6. Zhao, D., Dai, Y., Zhang, Z., Computational intelligence in urban traffic signal control: a survey. *IEEE Trans. Systems, Man, and Cybernetics—Part C: Applications and Reviews* 42(4), 485-494, 2012.
7. Gokulan, B. P., Srinivasan, D., Modified symbiotic evolutionary learning for type-2 fuzzy system. *IEEE Trans. Intell. Transp. Syst.* 8(2), 353-362, 2014.
8. Srinivasan, D., Choy, M. C., Cheu, R. L., Neural networks for real-time traffic signal control. *IEEE Trans. Intell. Transp. Syst.* 7(3), 261-272, 2006.
9. Hamilton, A., Waterson, B., Snell, I., Andrews, M., Performance evaluation of stage skipping and new data sources compared against MOVA control. In: Proc. *17th IEEE ITSC,* pp. 2535-2540, 2014.
10. Yang, W., Bae, J. H., Oh, Y., Chong, N. Y., You, B. J., Biologically inspired control for robotic arm using neural oscillator network. In: Proc. IEEE/RSJ IROS, pp. 135-141, 2009.
11. Geroliminis, N., Skabardonis, A., Identification and analysis of queue spillovers in city street networks. *IEEE Trans. Intell. Transp. Syst.* 12(4), 1107-1115, 2011.
12. Zhang, X., Effects of queue spillover in networks considering simultaneous departure time and route choices. *Transportation Planning and Technology* 36(3), 267-286, 2013.
13. Kandel, E. R., Schwartz, J. H., Jessell, T. M., Siegelbaum, S. A., Hudspeth, A. J., *Principles of Neural Science.* McGraw-Hill Education, 2012.
14. Peláez, F. J. R., Andina, D., The koniocortex-like network: a new biologically plausible unsupervised neural network. *Artificial Computation in Biology and Medicine* , 9107, 163-174, 2015.
15. Gil, A. F. A., Espinosa, J., Espinosa, J. E., TraCI4Matlab: Re-engineering the Python implementation of the TraCI interface. In: Proc. SUMO2014, pp. 145-155, 2014.
16. Keller, E., Saklas, J., Passenger car equivalents from network simulation. *Journal of Transportation Engineering* 110(4), 397-411, 1984.