Self-Organizing Traffic Lights: A Pedestrian Oriented Approach

Jessica S. Souza[1], Cesar A. M. Ferreira[2], Cassio E. dos Santos Jr[3], Victor H. C. Melo[4], William Robson Schwartz[4]
Computer Science Department, Federal University of Minas Gerais, Belo Horizonte, Brazil
{jessicasena,amf,victorhcmelo,cass,william}@dcc.ufmg.br

***Abstract*—The traffic light is one of the valuable devices to control the vehicular and pedestrian traffic. One of its main issues is that several traffic lights might be improperly calibrated once they do not consider the differences in pedestrian mobility from region to region. As each region presents different pedestrians with different characteristics, there is a need for automatic approaches. In this work, we propose a new approach to automatically adjust the pedestrian traffic light program to provide greater safety for pedestrians and to allow a better flow of the traffic. We deal with two challenging cases in transport engineering literature. The first case happens when pedestrians with reduced speed cannot cross the street within the available time. The second case happens when the traffic light for pedestrians remains open for a long time even when there are no pedestrians waiting to cross. Our proposed approach consists of a new segmentation step based on the pedestrians' distribution map; a pedestrian tracking step based on a Kalman Filter model and a new association metric; and, finally, a module that uses the information provided by these two previous steps to control the self-manageable traffic light. The experimental evaluation shows that the proposed approach allows to minimize cases in which pedestrians are crossing the street and the traffic light turns red.**

***Keywords*-Pedestrian tracking; self-manageable traffic light.**

I. Introduction

Brazilian cities have been modified by the influence of automobile traffic. The growth of the private car fleet affects urban centers in a negative way, creating disharmony between pedestrians and vehicles. Traffic light is one of the valuable devices for the control of vehicular and pedestrian traffic, used to regulate, warn, or guide traffic [1]. However, several traffic lights might be improperly calibrated because they do not consider the differences in pedestrian mobility from region to region within the city.

The 70th article of the Brazilian Traffic Code states that, in case there is a crosswalk available, the crossing priority will be in accordance with the emitted traffic light for pedestrians and vehicles, where pedestrians always have priority on completing the crossing, even if the traffic light changes from pedestrian traffic to car traffic. On these occasions, more than the discomfort and embarrassment suffered by the pedestrian, the increase of the risk of accidents is a major concern, especially for those with reduced mobility.

[1]Undergraduate student responsible for the tracking and Traffic Light Manager approaches.

[2]Undergraduate student responsible for the crosswalk segmentation.

[3]Collaborator responsible for the association metric.

[4]Advisor and co-advisor.

Many studies seek to analyze the optimum pedestrian speed. FHWA [1] shows that the ideal pedestrian speed is 1.22 m/s, a value accepted by different laws around the world. However, there is not a consensus in the research community. For instance, Silva *et al.* [2] establish that 1.22 m/s is the average speed to cross the street, with a minimum of 0.63 m/s to a maximum of 1.83 m/s, indicating the existence of several factors which affect the speed of pedestrians, such as age and the vehicles average speed. Hence, we can notice that the value of 1.22 m/s is not the best pedestrian speed estimation due to different pedestrian types. Besides, each region in a city presents different characteristics, such as hospital regions, which have a higher number of pedestrians with mobility problems. Due to the large number of cases, it becomes hard to measure the pedestrian speed manually. Thus, there is need for automatic approaches.

Current automated approaches are divided into two groups. The first group, called *green-waves*, works coordinating a series of traffic lights to allow continuous traffic flow over several intersections in one main direction. The second, called *self-organizing traffic lights*, works dynamically and automatically coordinating traffic lights considering the traffic conditions. Both approaches have their limitations, as described in Section II-A, and mainly, do not give preference to pedestrians.

In this work, we propose the Traffic Light Manager (TLM), a framework to automatically adjust the traffic light program by changing the light signal time to provide more safety to pedestrians crossing the street. We deal with two challenging cases in transport engineering literature. The first case happens when pedestrians with reduced speed cannot cross the street within the available time, i.e., their estimated crossing time exceeds the remaining green time. Thus, the time of flashing red – upraised hand, in English language countries – will be increased according to the need of the pedestrian who cannot achieve a crossing speed of 1.22m/s. The second case happens when the traffic light for pedestrians remains open for a long time even when there are no pedestrians waiting to cross, in which by watching the sidewalk the green light time might be increased for cars.

This work proposes an approach where the traffic light is self-organizable and makes decisions based upon computer vision tools. As pedestrian detection is important for several steps of our methodology, we employ the HOG detector [3] for such purpose. As pedestrian tracker we employ the Kalman filter due to its simplicity, optimality, tractability and robustness [4]. Since TLM require information of whether detected pedestrians lies on the crosswalk, we propose a segmentation step to determine the sidewalk and crosswalk regions of a monitored street. To perform such segmentation with robustness and better localization, we propose to use the pedestrian's distribution over a locality map.

We validate the proposed method in two datasets. First, we evaluate the pedestrian tracking performance on the PETS dataset [5]. Then, we evaluate the proposed self-organizing traffic light in a challenging dataset provided by Gualberto *et al.* [6], recorded under influence of variations of illumination and shadows. We show that the traffic light manager approach is able to increase the time of flashing red when there are pedestrians within the street.

The remaining of this work is organized as follows. In Section II, we reviewed the literature on the methods used. In Section III, we describe our model and its individual components. Finally, the proposed method is experimentally evaluated in Section IV.

II. Related Work

In the following sections we discuss methods to coordinate traffic lights (Section II-A) and object tracking (Section II-B).

A. Traffic Light Coordination

There are two major types of approaches in literature to coordinate traffic lights: *green-waves* and *self-organizing* [7]. Green-waves consist in determining the green light time in traffic lights between intersections according to the expected time travel between those intersections. The green light time is chosen considering the minimization of the time travel, often performed offline, for periods of the day such as morning, afternoon, rush hours, sportive events, weekends. This way, vehicles that follow the direction of successively green lights usually do not require stopping. Green light times, however, are usually optimized considering an average situation, which may not always result in optimal time travel. If the vehicles are moving slower than expected, for instance, the time determined to the green lights may, in fact, increase the average time travel.

Self-organizing traffic lights [7]–[9] consider the actual state of the traffic to determine the time of the green lights. Since optimizing the time travel for several intersections in a large urban area is computational expensive and unfeasible to calculate in real time, the optimization is performed in groups of few intersections. The advantage of approaches based on self-organizing traffic lights is that green lights can adapt when the traffic condition changes. However, self-organizing traffic lights usually require more sensors to proper measure variables in intersections, such as number of vehicles in the intersection, their average speed, and state of the traffic lights in the neighborhood.

Several approaches have been proposed to measure parameters for the self-organizing traffic lights, including car-to-car communication [10], magnetic loops [11], and computer vision techniques [12]. Although works in literature focus on coordinating traffic lights oriented to vehicles, in this work, we focus on developing a self-organizing traffic light oriented to pedestrians.

B. Pedestrian Tracking

The pedestrian tracking presents several challenges related to partial occlusion and change in the appearance of the pedestrian due to, for instance, changes in the pose or in the lightning conditions. Some approaches consider online models to adaptively learn the appearance of the tracked subject [13], [14]. Such approaches, however, should carefully select samples of the subject being tracked to update the online model. Otherwise, accumulated errors from samples acquired using the online model can drift the model towards learning the appearance of the background in the scene. The drifting problem can be solved considering *tracking-by-detection* [15], [16], where only samples filtered by the pedestrian detection are presented to update the online model. The best results in tracking-by-detection are acquired when samples of the background are considered as counter-examples when training the detector [14].

In general, pedestrian tracking approaches consist in a motion model, an appearance model, and a tracking algorithm responsible to determine the subject location based on the models of motion and appearance [17], [18]. Regarding the appearance model, there are several examples in literature, including methods based on superpixel [13], pixel intensity templates [19], HOG descriptor [14], Haar-like features [20], among others. However, the use of appearance model is not mandatory, some approaches [15], [16] rely only in a motion model and in the proper assignment of successively detections to track subjects. Regarding the motion model, there are approaches in literature that consider Gaussian distributions [13], particle filters [20], Kalman filters [21], among others.

III. Proposed Method

In this work, we propose a new approach able to automatically adjust the traffic light program by changing the light signal to provide greater safety for pedestrians and to allow better traffic flow (more details in Section III-C). The proposed approach requires information about the pedestrians to perform adjustments in the traffic light program, such as the need for increasing the time for pedestrian crossing. To provide such information, we propose a pedestrian tracking approach, based on Kalman filter, from which we obtain information such as the pedestrian's position and velocity (described in Section III-A). As our approach also needs to know the remaining distance of a pedestrian to the sidewalks, we propose a segmentation step based on the pedestrian's distribution map (described in Section III-B). These steps occur simultaneously and provide the required information to the manager, as illustrated in Figure 1.

A. Tracking

We use pedestrian tracking to improve the accuracy of detection and to estimate the pedestrian speed. The velocity is

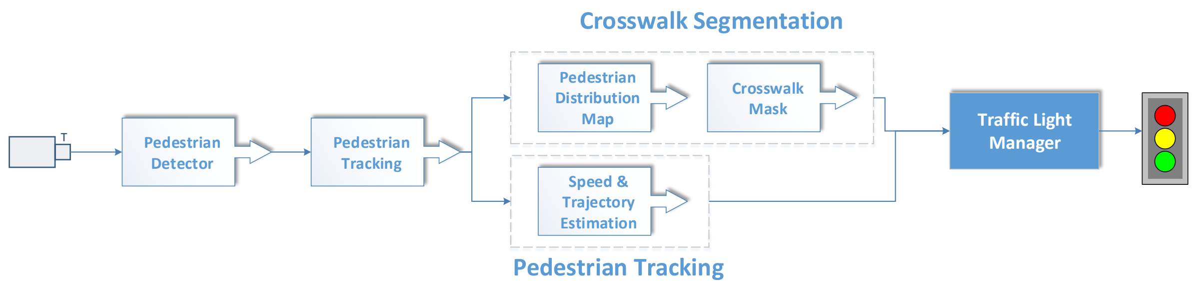

Fig. 1. Workflow of the proposed approach. The pedestrian position in each frame is determined in the pedestrian detector and pedestrian tracking modules. Then, the pedestrian position is used to estimate a distribution map where pedestrians walk when crossing the street and to estimate the speed and trajectory of these pedestrians to set the red flashing time in the pedestrian traffic light.

used to predict how long pedestrians that are in the crosswalk will take to reach the sidewalk. Therefore, if any pedestrian has low speed, e.g. pedestrians with reduced mobility, the time of the pedestrian traffic light will be increased proportionally. This prevents accidents that occur when the traffic light opens to the cars, and they move forward towards the pedestrians that are still crossing the road. We divided pedestrian tracking in three steps. First, we detect pedestrians using the HOG detector as described in [3]. Second, a motion model implemented using the Kalman filter is associated to each individual detected. Finally, we make associations between the detections of the new frame with individuals already been tracked.

1) Pedestrian Detection: Pedestrian detection is an important step for our methodology, since the remaining steps depends upon it. As the HOG detector presents lower computational cost and comparable false positive rate in our application, we employed it in this work. Nevertheless, one may consider any other pedestrian detector [22], more robust and/or faster ones, such as the PLS detector [23], the VeryFast detector [24], and the FPDW [25].

The HOG detector is a sliding-window based method consisting of the extraction of Histograms of Oriented Gradients (HOG). The HOG descriptor is extracted from a dense grid, which is obtained by dividing a detection window into overlapping blocks of size 16×16. Each block is divided into non-overlapping cells of size 8×8. For each cell, a 9-bin histogram of oriented gradients is computed, followed by a L2-norm block normalization with an optional clipping. The resulting histograms are then concatenated yielding a feature vector of 3,780 dimensions. Such feature vector is then presented to a linear SVM classifier.

2) Pedestrian Tracking: To model the motion of pedestrians using the Kalman filter, we consider the position (p_i, p_j) and velocity (v_i, v_j) of the center of the bounding box returned by the pedestrian detector. The (v_i, v_j) parameters are estimated considering successively detections presented to the Kalman filter. Then, the prediction of the next bounding box of a pedestrian is calculated according to Equation 1, where k is the current state, $k-1$ is the previous state, A is the state transition matrix, and w is the process noise.

$$X_k = Ax_{k-1} + w_{k-1} \tag{1}$$

The detections of the new frame may belong to one of two categories: a detection of a new pedestrian coming into the crosswalk or a new detection of the pre-existing pedestrian. In the first case, a Kalman filter model is created for each new subject. This new subject is tracked across the crosswalk and his/her velocity is taken into account when the traffic signal for pedestrians is about to close. In the second case, the new detection is associated with a pre-existing subject. To discover whether the new detection belongs to some pre-existing subject, we use a metric based on average and variance that will be explained later.

In addition to the aforementioned cases, the pedestrian might be occluded in the scene, which creates two cases to be processed. In the first case, the crosswalk may have a point of occlusion, for instance, as under the shade of a tree, or the pedestrian can stay occluded by another pedestrian. In this case, the subject motion model continues predicting, and the pedestrian can still be tracked. In the second scenario, the pedestrian may have left the crosswalk, and went into the sidewalk, being safe and no longer need to be tracked. Since we do not aim at identifying the individuals and only provide a safe crossing, we do not need to keep tracking the subjects after they reach the sidewalk. Thus, we fix N as the number of frames that the pedestrian is then regarded outside the crosswalk and not only occluded. This N is set according to the size of the crosswalk.

3) Association Metric: Given n Kalman motion models learned considering detections from the past frames and d detections of the current frame, the objective of the association metric is to link each one of the d detections to one, and only one, subject relative to one of the n motion models.

The association is performed as follow: the minimum distance m between a detection from the current frame and the predicted state of each Kalman motion model is compared to the expected distance of the Kalman motion model being considered. The predicted state of the Kalman motion model is given in Equation 1. The expected distance between the prediction of a Kalman motion model and a detection is calculated considering the exponentially weighted moving average and variance, presented in Equation 2.

$$\begin{aligned}
\epsilon &= m - \mu_t \\
\mu_{t+1} &= \mu_t + \alpha \times \epsilon \\
\sigma^2_{t+1} &= (1-\alpha) \times (\sigma^2_t + \alpha \times \epsilon^2)
\end{aligned} \tag{2}$$

The association is performed only if the probability of m being draw from the same distribution D of distances between predictions and detections of the Kalman motion model is above p. Considering D normally distributed, the aforementioned comparison is calculated according to Equation 3.

$$m < \mu_t + k * \sigma \tag{3}$$

When creating new distribution models, we set μ to a maximum distance in pixels by which a pedestrian cannot move between two frames. Higher initial values of μ, however, may incorrectly associate the detection of a subject being tracked in initial frames, when μ and σ^2 did not converged yet. The initial value of σ^2 is set to zero, although, a fast growth is observed while μ is converging.

B. Segmentation Based Upon Pedestrian Distribution Map

We propose a segmentation step based on a pedestrian distribution map to estimate the crosswalk's borders with the sidewalk and the regions presenting pedestrian traffic. Such segmentation is required to determine whether a pedestrian is in the street or in the sidewalk. The segmentation is performed using the speed and position information generated by the tracking step. The speed vector contains the pedestrian speed on the x-axis and on the y-axis, we compute the norm of this vector, to determine whether the pedestrian is moving or not. If the norm of this vector is less than a threshold, then the pedestrian is stationary and is more likely to be on the sidewalk waiting for crossing. Otherwise, if the pedestrian exceeds the threshold, he/she is likely to be moving and most likely to be at the crosswalk.

The pedestrian's distribution map consists of a matrix accumulated over time, in which a position is incremented according to the detected pedestrian. We use the pedestrian's distribution map to segment the regions belonging to the crosswalk and the regions that belongs to the sidewalks. During a crossing, it is expected that the largest concentration of moving pedestrians will be on the crosswalk, while stationary pedestrians will be at the sidewalk.

C. Traffic Light Manager (TLM)

Given the crosswalk location, the TLM verifies whether a pedestrian p is in the crosswalk, and whether the crossing time duration of p is higher than the remaining green time of the Pedestrian Traffic Light.

The crosswalk location is given by a binary mask from semaphore surveillance video. Let M be a matrix that representing this mask the locations where $M_{ij} = true$ determine the crosswalk area. The crossing time of p is given by the equation of uniform rectilinear motion $t = \frac{d}{s}$, where d is the distance between p and the end of the crosswalk, and s is the crossing speed of p. For calculated de distance d, we need determine the pedestrian direction, since end of the crosswalk is relative to the direction to which the pedestrian is moving. To determine the pedestrian direction, we calculate the angle θ between the vector u that represents crosswalk direction , and the vector v that represents the pedestrian position. The angle θ is given by Equation 4. If θ is negative we conclude that the pedestrian is moving to the left of the crosswalk, and if θ is positive we conclude that he is moving to the right.

$$\theta = \frac{u \cdot v}{||u|| \cdot ||v||} \tag{4}$$

The distance $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ where (x_1, y_1) is the position of the p, and (x_2, y_2) is the pixel of the crosswalk end border that is more distant from the pedestrian. This comparison between pedestrian and the more distant pixel, ensures the safety of the pedestrian crossing even if he makes the longest trajectory to exit the crosswalk. The speed of p is given by the length of the velocity vector v. The vector v is given by the Kalman model associated with it, and the computation of the length of v is given by $||v||$.

Given the equation and definitions above, if the crossing time t of the pedestrian p is greater than the remaining time r of the open semaphore for pedestrian crossing, the state red-flashing light for pedestrians will increment in n frames and the traffic light for cars will remain closed, where $n = t - r$ ensuring a safety crossing for pedestrians. Since pedestrians are tracked along time by pedestrian tracking. Therefore, if the speed of the p change and its crossing time become shorter than the remaining green time, the pedestrian traffic light will not be incremented. The TLM will increase the traffic light according to the greatest need for increment. Thus, if there is another pedestrian who has crossing time greater than the time of p, the traffic light will be increased with the time required for this slower pedestrian.

IV. Experiments

In this section, we present experiments to evaluate the steps of our proposed approach. First, we demonstrate the applicability of the proposed tracking method for tracking pedestrians in the crosswalk. Second, we evaluate the TLM compared to the real traffic signal, which does not dynamically adapt to pedestrian and vehicle flow.

A. Experimental Setup

The parameters of the proposed approach include the parameters from the HOG detector, Kalman filter, and association metric. Regarding the implementation, we use the Smart Surveillance Framework (SSF) [26], since it contains a public implementation of the HOG detector.

Pedestrian Detector. We tested several combinations of HOG detector input parameters to obtain a more robust method for each specific situation. To evaluate the pedestrian detection, we set the horizontal and vertical stride of the sliding window

Fig. 2. In the left image, we show a common situation in the region where the dataset [6] was recorded, elderly pedestrians and mothers with babies on their lap crossing in the crosswalk. In the right image, we show one of the three sequences of the PETS dataset, the challenges of this dataset are occlusion and pedestrians crowd. PETS was used only to evaluate the tracking proposed method and the dataset [6] was used to evaluate the TLM.

to 6 pixels and scale step to 0.5. These parameters control how much displacement is given between two detection windows and between different scales. To evaluate the TLM, we set the horizontal and vertical stride to 8 pixels and the scale to 1.05.

Association Metric. In the tracking and traffic lights manager evaluation, we fix the parameter μ as 0.1, and we evaluate two different values for the α parameter, 15 and 25. The α parameter set as 15 becomes the association more restrictive, while as 25, the association is more flexible.

Kalman Filter. We divide the evaluation into two groups, one that the positions are given by the Kalman predicted state and other that the positions are given by the estimated state. Within each group, we present the best result by testing several different parameters from the HOG detector and from the association metric.

Datasets. The experiments were conducted on two datasets, show in the Figure 2. PETS 2009 Dataset S2 and in a dataset composed of urban crosswalk images acquired from a hospital area [6]. The former is used to evaluate the proposed tracking method, while the latter is used to evaluate the TLM. PETS 2009 Dataset S2 is a standard dataset widely used for tracking evaluate. This dataset have three scenarios with three difficult levels, L1, L2 and L3, respectively. Scenario L1 consists of a sequence of 784 frames and contains a sparse crowd sequence where some pedestrians walk through a courtyard. The scenarios L2 and L3 consist of a sequence of 435 and 239 frames, respectively. In these scenarios, the difficult level increases as they present pedestrian crowd and many occlusion cases. In the evaluation of the TLM, we use a video recorded near a hospital area in Belo Horizonte/Brazil [6]. For this purpose, we labeled every sixth frame, resulting in a total of 3775 labelled frames. The information annotated is the traffic light signal (green, red, flashing red). For the frames where the signal is red or flashing red, we also annotate whether or not the pedestrian is present in a crosswalk. This was done to evaluate our method, the information about the light signal state is considered to increase the time of the red flashing lights whenever our approach detect pedestrians in the crosswalk.

B. *Tracking Evaluation*

We evaluate the proposed tracking considering four parameter setups, which consist in the combination of two values for μ_0, 15 and 25, and predicted or estimated state of the Kalman filter. The setups are presented in Table I.

TABLE I
SETUPS CONSIDERED IN THE COMBINATION OF KALMAN FILTER AND HOG DETECTOR.

	Tracking	Association Metric
SetupA	Prediction	$\mu_0 = 25$
SetupB	Prediction	$\mu_0 = 15$
SetupC	Estimated	$\mu_0 = 25$
SetupD	Estimated	$\mu_0 = 15$

Results considering miss rate and false positives per-image (FPPI), for each setup and in the PETS 2009 dataset, are presented in Table II. We shows in Table II the results of comparison of the our proposed methods against the HOG detector. Although our proposed tracking method achieved a smaller recall rate than the HOG detector in the L1 sequence, it achieved higher recall rates in the L2 and L3 sequences (*i.e.*, more difficult sequences) because it is better to handle occlusion than the detector by itself.

TABLE II
COMPARISON OF HOG DETECTOR AND OUR PROPOSED TRACKING METHOD. RECALL IS COMPUTE AT 1 FPPI

	Scenario L1	Scenario L2	Scenario L3
HOG Detector [3]	0.679	0.227	0.305
Tracking(A)	0.497	0.274	0.135
Tracking(B)	0.515	0.274	0.336
Tracking(C)	0.462	0.222	0.324
Tracking(D)	0.483	0.274	0.317

C. *Traffic Light Manager Evaluation*

We evaluate the self-organizing traffic lights proposed method. For this purpose, we use six sequences of the traffic signal states (green, flashing red, red) of the dataset in [6]. Our major concern is to improve the safety of the pedestrian crossing allowing the traffic light to self-organize according to pedestrian speed at that region of the city. In Figure 3 we present results indicating the number of pedestrians in the crosswalk when the pedestrian traffic light turns red and the time increased to allow the pedestrians to safely cross the street.

According to Figure 3, best results are achieved when increasing around 40 seconds (6.66 seconds on average in each red flashing light cycle), when all pedestrians make to cross the street in the red flashing light. Table III show time increased in each sequence. The results of the TLM show the feasibility of the proposed approach. However, we do not consider the impact of the increase in time for the red flashing light on the vehicle flow. To balance between safety and vehicle flow, we suggest varying the additional time in Figure 3.

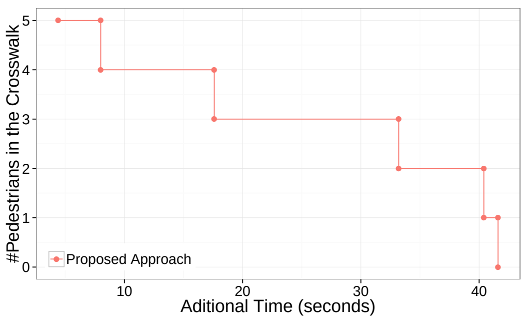

Fig. 3. Number of pedestrians in the crosswalk when the pedestrian traffic light turns red compared to the time given to pedestrians to cross the street. Better approaches present few pedestrians in the crosswalk and few additional time.

TABLE III
TIME (IN SECONDS) ADDED TO EACH RED FLASHING LIGHT SEQUENCE TO ALLOW ALL PEDESTRIANS TO SAFELY CROSS THE STREET.

Seq. 1	Seq. 2	Seq. 3	Seq. 4	Seq. 5	Seq. 6
6.4	6.6	7.0	6.6	7.4	11.0

V. CONCLUSION

We proposed and evaluated an approach of self-organizing traffic light oriented to pedestrians based on computer vision techniques. To enhance the results of the pedestrian detection, we model temporal information considering the Kalman filter. Results show the feasibility in consider the proposed approach of self-organizing traffic light, which adaptively increase the time of different sequences of red flashing light based on the velocity of the pedestrians crossing the street. In future works, one may consider appearance models in our tracking approach since it has been shown to increase the accuracy of the tracking. A comparison of the proposed self-organizing traffic light with real pedestrian traffic lights may also be presented along with a study of impact of the the proposed traffic light in the vehicle flow.

REFERENCES

[1] Federal Highway Administration (FHWA), *Manual on Uniform Traffic Control Devices for Streets and Highways*, 2009.

[2] A. M. C. B. Silva, J. R. R. da Cunha, and M. R. d. C. A. Ferreira, "Velocidade Pedonal em Atravessamentos - Avaliação da Relevância dos Fatores Explicativos," in *Congresso de Ensino e Pesquisa em Transportes (ANPET)*, 2012.

[3] N. Dalal and B. Triggs, "Histograms of Oriented Gradients for Human Detection," in *Intl. Conference on Computer Vision and Pattern Recognition*, 2005.

[4] S. J. Julier and J. K. Uhlmann, "A new extension of the kalman filter to nonlinear systems," in *Aerosense*, 1997.

[5] "PETS 2013 Benchmark Data," 2013, online. Available in http://www.cvg.rdg.ac.uk/PETS2013/a.html.

[6] F. Gualberto, J. A. Dias, M. M. Thebit, and H. M. Barbosa, "Velocidade de pedestres em área hospitalar – um estudo exploratório," in *Congresso Nacional de Pesquisa e Ensino em Transporte (ANPET)*, 2013.

[7] C. Gershenson and D. A. Rosenblueth, "Modeling self-organizing traffic lights with elementary cellular automata," *Complexity*, 2009.

[8] N. Geroliminis and A. Skabardonis, "Identification and analysis of queue spillovers in city street networks," *Intelligent Transportation Systems*, 2011.

[9] D. Helbing and A. Mazloumian, "Operation regimes and slower-is-faster effect in the controlof traffic intersections," *The European Physical Journal B*, 2009.

[10] N. Maslekar, M. Boussedjra, J. Mouzna, and H. Labiod, "Vanet based adaptive traffic signal control," in *Vehicular Technology Conference*, 2011.

[11] M. Tubaishat, Y. Shang, and H. Shi, "Adaptive traffic light control with wireless sensor networks," in *Consumer Communications and Networking Conference*, 2007.

[12] A. Fernández-Caballero, F. J. Gómez, and J. López-López, "Road-traffic monitoring by knowledge-driven static and dynamic image analysis," *Expert Systems with Applications*, 2008.

[13] S. Wang, H. Lu, F. Yang, and M.-H. Yang, "Superpixel tracking," in *Intl. Conference on Computer Vision*, 2011.

[14] H. Pirsiavash, D. Ramanan, and C. C. Fowlkes, "Globally-optimal greedy algorithms for tracking a variable number of objects," in *Computer Vision and Pattern Recognition*, 2011.

[15] B. Benfold and I. Reid, "Stable multi-target tracking in real-time surveillance video," in *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, 2011.

[16] J. Berclaz, F. Fleuret, E. Turetken, and P. Fua, "Multiple object tracking using k-shortest paths optimization," *Pattern Analysis and Machine Intelligence*, 2011.

[17] G. P. F. Gisele M. Simas, "Using computer vision for 3d propabilistic reconstruction an motion," in *Computational Modeling (MCSUL)*, 2007.

[18] N. T. Siebel, "Fusion of multiple tracking algorithms for robust people tracking," in *European Conference on Computer Vision (ECCV)*, 2011.

[19] W. Zhong, H. Lu, and M.-H. Yang, "Robust object tracking via sparsity-based collaborative model," in *Computer Vision and Pattern Recognition*, 2012.

[20] B. Babenko, M.-H. Yang, and S. Belongie, "Robust object tracking with online multiple instance learning," *Pattern Analysis and Machine Intelligence*, 2011.

[21] K. Van Beeck, T. Goedemé, and T. Tuytelaars, "Towards an automatic blind spot camera: robust real-time pedestrian tracking from a moving camera," in *Conference on Machine Vision Applications*, 2011.

[22] P. Dollar, C. Wojek, B. Schiele, and P. Perona, "Pedestrian Detection: An Evaluation of the State of the Art," *Pattern Analysis and Machine Intelligence*, 2012.

[23] W. Schwartz, A. Kembhavi, D. Harwood, and L. Davis, "Human Detection Using Partial Least Squares Analysis," in *Intl. Conference on Computer Vision and Pattern Recognition*, 2009.

[24] R. Benenson, M. Mathias, R. Timofte, and L. Van Gool, "Pedestrian Detection at 100 Frames per Second," in *Intl. Conference on Computer Vision and Pattern Recognition*, 2012.

[25] P. Dollár, R. Appel, S. Belongie, and P. Perona, "Fast Feature Pyramids for Object Detection," *Pattern Analysis and Machine Intelligence*, 2014.

[26] A. C. N. Jr., C. E. dos Santos, R. Ferreira, and W. R. Schwartz, "Smart Surveillance Framework: A Versatile Tool for Video Analysis," in *IEEE Winter Conference on Applications of Computer Vision*, 2014.