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A Video-Based System Methodology for Detecting Red Light Runners

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Abstract

This paper presents a video-based system methodology for automatic red light runner detection on an image sequence. It extracts information regarding the state of the traffic light and vehicle motions without any physical or electronic connections to the traffic light control system or the buried loop detectors. The new methodology detects vehicle motions based on the virtual loop detector concept. A prototype has been built and tested in field trials. Results show that the prototype may be deployed at any junctions to detect multiple red light runners in multiple lanes. The methodology is also robust, reliable and effective in coping with hostile but realistic outdoor scenarios.

1 Introduction

The detection of the so-called 'Red Light Runners' (RLR), those who violate the red light, is one of the major issues in traffic management that has been studied by many around the world in the past[1-6]. The consequence of violating the red light could be fatal, and yet many motorists continue to do so without considering the potential hazard they may have caused. Recent research study has indicated that red light violation rate can be reduced substantially if Red Light Cameras (RLC) are installed strategically[7,8]. For example, in Scottsdale, Arizona, the red light violation rate dropped by 62% at intersections monitored by RLC[9]. Other case studies also confirmed similar potential benefits. However, even with such possible reduction in violation rate, annual figure for red light offences can still be startling. For instance, Hong Kong has been using RLC for a number of years. In 1997 alone, it has recorded 25,710 red light violation offences, from which 251 of them have resulted in serious accidents. The effect of red light monitoring and violation identification is positive without doubt. The question to be asked is whether this approach can be made more effective.

Most of the RLC employ a still camera and a number of buried loop detectors. The still camera must be mounted on a fixed camera post at some fixed location in relation to the traffic lights. It has to be electronically connected to the traffic light control system and two or more buried loop detectors at the junction in order to operate. Its principle is that when the traffic light is red and the loop detectors have detected one or more vehicles moving beyond the stop line into the junction at the same time, the camera takes two still photos of the vehicle(s). These photos are then used as evidences of the violation. RLC work well in most circumstances, perhaps except in some low light and adverse weather conditions. However, one major drawback of the RLC is the overall cost and their strict requirements. Unlike speed radar or laser gun that is extremely mobile, RLC are expensive to be widely deployed and their effectiveness as a law enforcement instrument or deterrent is reduced when their locations are known. For this reason, our motivation is to develop a new detection method that offers at least the same functionality of the RLC, but without the need to rely on the traffic light control or the buried loop detectors. It should also be mobile and cost-effective. Naturally, this implies the use of video processing and analysis techniques and technology.

In this paper, we present a video-based system methodology that performs automatic RLR detection on the traffic video without needing any signals from the traffic light system or the buried loop detectors. It primarily tackles two issues: (1) detect and construct a reliable traffic light sequence and (2) estimate vehicle motions beyond the stop line, while the light is red. In principle, the traffic lights in the FOV are first located by searching for all the red/yellow/green regions with aspect ratio close to unity and similar sizes. The spatial relationship between the lights is utilized to eliminate other regions, while the temporal relationship is utilized to confirm the former decision as well as construct the light sequence. This scheme essentially replaces the traffic light control signal.

The detection of vehicle motion beyond the stop line is by a direction-biased motion estimation algorithm. In our case, the full-search scheme is modified based on the known road direction and the concept of Virtual Loop Detector (VLD). The concept of VLD is to define regions on the video that can emulate the function of the physical buried loop detectors. Motion of the VLD may be estimated between two consecutive frames only in the direction of the road. With this, motions due to pedestrians, turning vehicles and shadows can be tolerated.

This approach has been implemented and evaluated using a number of traffic junction videos taken under different outdoor conditions, including one with the video camera mounted on an existing RLC post. In all our evaluation, the prototype identified all the RLR correctly. We also observed that the new methodology is also capable of accommodating a number of hostile but realistic situations: (1) minimum number of traffic light, (2) pseudo motions due to shadows, (3) poor contrast, (4) pedestrians crossing the road.

The organization of this paper is as follows. Section 2 overviews the new methodology. Section 3 details the algorithms developed. Section 4 presents the result of a field trial and discusses the performance of the methodology under those circumstances. This paper is concluded in Section 5.

2 Overview

A block diagram of the Red Light Video (RLV) methodology is depicted in Fig. 1. The input digital video is first analyzed by the Traffic Light Sequence Detection module, which consists of two sub-functions. The first one is the traffic light detection that locates the spatial coordinated of the centers of the red/yellow/green lights. The traffic light is then continually monitored and the light sequence updated over the entire video. The signals output from the light sequence construction are `stop`, `ready to go(RTG)`, `go` and `ready to stop(RTS)`.

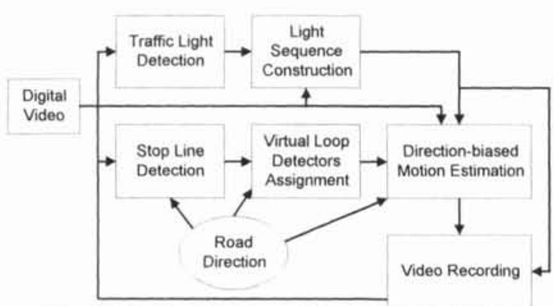

Fig. 1: Block diagram of the RLV Methodology

Secondly, the input video is analyzed by the Vehicle Motion Detection module, which consists of three sub-functions namely: Stop Line Detection (SLD), Virtual Loop Detectors Assignment (VLDA) and Direction-biased motion estimation (DME). SLD only needs one frame if the stop line is not blocked by any objects. From the stop line, the VLDA defines a number of VLD beyond it. Each VLD is a group of pixels in which the size is depending on how close-up the camera view is. This approach of grouping pixels into blocks is borrowed from the standard block-based motion estimation used in video coding where motion estimation is performed on the blocks instead of individual pixel. This also suits the concept of emulating the buried loop detectors. Given the VLD, and the knowledge of the state of the traffic light and the road direction, the DME considers the VLD between two consecutive frames. This approach attempts to find the best match in terms of Mean-Absolute-Difference (MAD) in the forward direction of the road only, for each VLD. The estimated motion vectors (MV) are weighted corporately for determining whether they together represent a moving vehicle or something else. The criteria employed here are that if more than half of the MV are larger than half of the mean motion vector of their corresponding VLD, and are in the direction of the road, then they represent a moving vehicle. This implies a vehicle is moving beyond the stop line while the light is red, or a red light runner. The frames of the offence can either be stored locally as record of the event or transmitted via a communication medium to a remote location.

3 Algorithms

Definitions of Regions

Let us assume the video consists of color images, I_t, defined in the HSV (Hue-Saturation-Brightness) space as given by Eqt. (1):

$$I_t = \left\{ f_t(x,y) = \begin{bmatrix} f_{t,H}(x,y) \\ f_{t,S}(x,y) \\ f_{t,V}(x,y) \end{bmatrix} \right\}, \tag{1}$$

where (x,y) denotes the image spatial coordinates and $f_{t,H}(x,y)$, $f_{t,S}(x,y)$ and $f_{t,V}(x,y)$ denote the hue, saturation and brightness components respectively. From this, white (W), red (R), yellow (Y) and green (G) regions are defined as follows:

$$R_{W,k} = \{g(x,y) \in I_t : g_S(x,y) < t_s \text{ and } g_V(x,y) > t_v\}, \tag{2}$$

$$R_{R,k} = \{g(x,y) \in I_t : |g_H(x,y)| < \varepsilon \text{ and } g_V(x,y) > t_v\}, \tag{3}$$

$$R_{Y,k} = \{g(x,y) \in I_t : \left|g_H(x,y) - \tfrac{\pi}{3}\right| < \varepsilon \text{ and } g_V(x,y) > t_v\}, \tag{4}$$

$$R_{G,k} = \{g(x,y) \in I_t : \left|g_H(x,y) - \tfrac{2\pi}{3}\right| < \varepsilon \text{ and } g_V(x,y) > t_v\} \tag{5}$$

where t_s, t_v and ε are threshold values; $R_{\psi,k}$ are connected regions that $R_{\psi,k} \cap R_{\psi,j} = \phi$, for all k and j, $k \neq j$ and $\psi = W, R, Y, G$.

Traffic Light Detection

First, the positions of the *red* lights are detected using Eqt (2) over a number of image frames. Assume in each frame, n_R number of *red* regions, $R_{R,k}$ for $k=1,\ldots,n_R$, are detected, from which the aspect ratio of $R_{R,k}$ may be computed by

$$\alpha(R_{R,k}) = \frac{width(R_{R,k})}{height(R_{R,k})}, \tag{6}$$

where $width(R_{R,k})$ and $height(R_{R,k})$ denote the width and height of $R_{R,k}$ respectively. As some of these *red* regions are due to other objects in the FOV, the aspect ratio can be used to discriminate them from the red lights by considering only those $R_{R,k}$ with $\alpha(R_{R,k}) \approx 1$.

Then, the *yellow* regions are detected by Eqt. (3) in a similar manner, where those $R_{Y,j}$ with $\alpha(R_{Y,j}) \approx 1$ are retained, for $j=1,\ldots,n_Y$. As the *red* and *yellow* lights are spatially related, $R_{R,k}$ and $R_{Y,j}$ represent a potential traffic light pair, if and only if $R_{Y,j}$ is vertically and immediately below $R_{R,k}$, and $width(R_{R,k}) \approx width(R_{Y,j})$.

Lastly, the *green* lights are detected differently because of their low brightness and contrast, variations in size and shape, and that many roadside objects are green. For *red-yellow* light pair obtained after the second step, a region is interpolated vertically below the *yellow* light with center-to-center distance same as the *red-yellow* pair, and of similar size and aspect ratio. If *green* sub-regions are found within this region using

Eqt. (4), a complete traffic light is formed as $TL_m=\{R_{R,m}, R_{Y,m}, R_{G,m}\}$, where $R_{R,m}$, $R_{Y,m}$ and $R_{G,m}$ denote the *red*, *yellow* and *green* lights respectively. If *green* sub-regions are not found, the *red-yellow* light pair will be discarded. From all the TL_m found, the one with the largest size is selected for subsequent analysis.

Light Sequence Construction

To construct the light sequence from the selected traffic light, we compute the average brightness of the lights when they are first detected:

$$\overline{B}_\psi = \frac{1}{S_\psi}\sum g_V(x,y)\Big|_{g(x,y)\in R_\psi}, \qquad (7)$$

where S_ψ for $\psi=R,Y,G$ are the size of the *red*, *yellow* and *green* regions. At frame f, the average brightness of the lights, $\overline{B}_{\psi,f}$ for $\psi=R,Y,G$ are computed using Eqt. (7), from which the state of the traffic light is calculated as

$$state = \begin{cases} ON & \overline{B}_{\psi,f} > \frac{1}{2}\overline{B}_\psi \\ OFF & otherwise \end{cases} \qquad (8)$$

These states are then compiled as in Table 1 to generate the light sequence: `stop`, `RTG`, `go` and `RTS`.

	Red	*yellow*	*green*
`Stop`	***ON***	*OFF*	*OFF*
`RTG`	***ON***	***ON***	*OFF*
`go`	*OFF*	*OFF*	***ON***
`RTS`	*OFF*	***ON***	*OFF*

Table 1: Four states of a traffic light

Stop Line Detection

First of all the white regions, $R_{W,k}$ in a frame are detected using Eqt. (2), for $k=1,\ldots,n_W$, where n_W is number of white regions detected. Second, the detected regions, $R_{W,k}$ are thinned and transformed to ρ–θ space using Hough transform, from which the length, $l_{W,k}$ and orientation, $\theta_{W,k}$, of the thinned regions (lines) are calculated. The stop line, l_W, is determined as the longest line, $\max(l_{W,k})$, that sustains the largest angular deviation from the road direction, $\max(|\theta_{W,k}-\theta_{road}|)$, where θ_{road} is the road direction.

Virtual Loop Detectors Assignment

Let us define the VLD's in frame f as $N\times N$ blocks given by $s_{i,f}(n_x,n_y)$ for $i=1,\ldots,M$, where M is the number of VLD in the frame. The initial assignment of these VLD starts from the stop line. For an image sequence of N_v frames with vehicles passing the junction and assume there is only translation motion between consecutive frames, the *MAD* between two VLD from frames f and $f+1$ is given by

$$MAD(d_x,d_y) = \frac{1}{N^2}\sum_{\forall(n_x,n_y)}\left|s_{i,f}(n_x,n_y)-s_{i,f+1}(n_x+d_x,n_y+d_y)\right|, \qquad (9)$$

and $d_x,d_y : |d_x,d_y|<r$, $|\angle(d_x,d_y)-\theta_{road}|\le\beta$, where r is the search range and β is a limited search angle. Therefore the motion vector is calculated as

$$v_{i,f} = (d_x,d_y)^T = \arg\left(\min_{(d_x,d_y)} MAD(d_x,d_y)\right) \qquad (10)$$

The mean and standard deviation of the motion vectors' magnitude ($\rho_{i,\mu}$, $\rho_{i,\sigma}$) and orientation ($\theta_{i,\mu}$, $\theta_{i,\sigma}$) are computed over N_v. Those VLD with minimum standard deviation in both magnitude and orientation are chosen as the final set of VLD for vehicle motion estimation as depicted in Fig. 2.

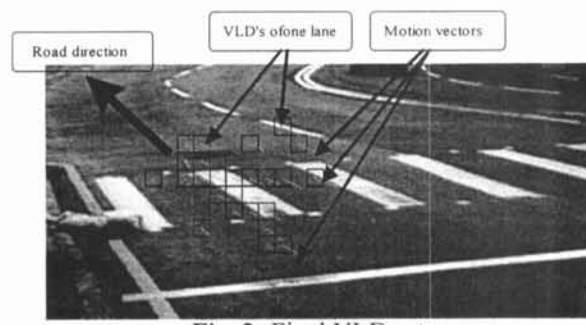

Fig. 2: Final VLD set

Direction-biased Motion Estimation

To estimate vehicle motions in the junction, we first compute the motion vectors $v_{i,f}$ over the final VLD set. The result is also depicted as straight line segments in Fig. 2. For detecting red light runners, we have the following conditions:

$$c_i = \begin{cases} 1 & |v_{i,f}| > \frac{1}{2}\rho_{i,\mu} \text{ and } \angle v_{i,f} \approx \theta_{road} \\ 0 & otherwise \end{cases}, \qquad (11)$$

for $i=1,\ldots,N_B$ where N_B is the number of VLD per lane in the final set. Eqt. (11) means that for each VLD, if its MV magnitude is larger than half of the mean MV magnitude calculated previously and its direction is aligned with the road direction, then it is possible that part of a vehicle moves over this VLD. If $\sum_{i=0}^{i<N_B-1} c_i > \frac{1}{2}N_B$, then a RLR is detected in that lane.

4 Trials and Results

The new RLV methodology was implemented and a prototype was constructed. The result presented here was take from one of the many trials we have conducted so far. The trial site is a typical junction in Hong Kong with two lanes in each direction. The RLV prototype was mounted on a 4 feet tripod by the roadside, without any connections to the traffic light control system or the buried loop detector circuit. The trial was conducted on a randomly chosen morning when it was reasonably bright. After the prototype was setup, it was left running for 30 minutes without interruption. The whole event was recorded on tape for off-line inspection. During the trial, the traffic light changed a number times and there were fast and slow moving vehicles of all kinds and pedestrians crossing the road. Over this period, a number of red light runners were detected and these cases were confirmed violations by the visual inspection.

Fig. 3 depicts one of the cases of red light running by a minibus. It should be noted that there were two traffic lights visible, one in front of the other. In fact, only the one closest to the camera was used for constructing the traffic light sequence. The contrast of the stop line is fine and there were a bit of shadow cast by the roadside objects and the vehicles themselves. Even under these conditions, the stop line was detected and the VLD was determined as in Fig. 2. The RLR was correctly identified by this method with information indicating data, time, frame number and the time it was detected (1.86 seconds) after the light turned red. The image on the left also depicts the minibus was clearly beyond the stop line while the light is red.

5 Conclusions

In conclusion, we have presented a novel methodology for detecting red light runners in this paper. Compare the results of this method with existing RLC, it is observed that it is superior in a number of areas. First, without needing any connections to the traffic light and buried loop detectors, this method offers a mobile and cheaper solution. One of our other trials was having the prototype mounted on an existing RLC camera post. It worked equally well. Second, the new method provides more than 10 frames of the RLR incident as compared with only 2 photos in the RLC. This is advantageous if automatic license plate recognition is to be performed. Third, the video analysis concept employed in the methodology can be further developed into a multi-functional architecture where other traffic parameters may be calculated or estimated, e.g., vehicle speed and vehicle count.

From the trial results, we also observed that the methodology is able to cope with a number of hostile but realistic situations. Firstly, it handles the traffic light detection very well under outdoor condition. It detected all the lights and built the light sequence around from the one closest to the camera as expected. Secondly, it deals with the pseudo motions and poor contrast appropriately and adequately. Such pseudo motions were the result of nearby objects, which affected the accuracy of the motion vectors. However, the motion estimation criteria seem to be robust enough to tolerate this problem. The poor contrast has adverse effect on the stop line detection and the virtual loop detectors assignment. However, the trial results showed that this could also be tolerated too.

6 References

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Fig. 3: Red light running by a minibus