A Vehicle Tracking System Using PCA and Adaptive Resonance Theory

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Abstract: - This work presents vehicle detecting and tracking system from a sequence of images. The system utilizes ART (Adaptive Resonance Theory) network for segmentation and recognition. By applying log-Gabor filters to the initially detected vehicle, the resulting filtered vehicles are fed into the network which can automatically recognize salient features of vehicles by analyzing theirs principal components. This unsupervised network allows the system to efficiently perform tracking in dynamic environments where shapes and sizes of vehicles are changing all the time. The proposed system can also track multiple vehicles simultaneously. Results and discussions are described.

Key-words: Vehicle tracking, Log-Gabor filter, Principal component analysis, Adaptive resonance theory network, Image processing, Driver assistance system

1 Introduction

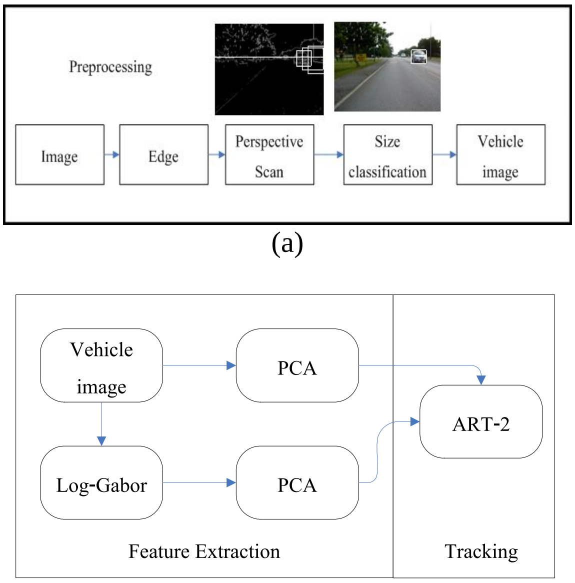
Nowadays, there are many kinds of technology for safety and reducing accidents on the road. Statistically, most of accidents come from vehicle driver. Driver assistance system then has been focused to warn the driver for a chance of an accident to be happening or to control vehicle for avoiding any wreck. Generally, various kinds of sensors can be installed on a vehicle to detect surrounding objects which mostly are other vehicles or pedestrians. There are two types of these sensors: active sensor and passive sensor. Active sensors, such as lidar, radar, and laser, are capable of scanning areas around the vehicles, but they have low resolution, slow scan speed, and expensive. Passive sensors, such as camera, are simple to use, less expensive, high resolution, and useful for other simultaneous tasks, e.g. lane detection and traffic sign recognition.

Researches of vehicle tracking can be categorized into three groups [1]: optical flow based, model based and feature based vehicle tracking. The optical flow based vehicle tracking utilizes useful information from optical flows. This approach is efficient but required to perform with high resolution images. The model based vehicle tracking is to estimate model in the image plane and use it for matching and tracking. The feature based vehicle tracking deploys salient features of vehicle such as edges, textures, and coners, for matching vehicle in the image. In [2], information of HSV is applied for tracking vehicle using both hue level and edge image for building statistic model of vehicle. In [3], feature vectors of vehicles are constructed using areas and positions of rectangle in the image, and averaging color of vehicle. The Kalman filter is used to predict position of vehicle in the next frame. In [4], Kanade-Lucas-Tomasi (KLT) feature tracker is exploited with Kohonen self-organizing map (SOM) network for tracking vehicles. Input of the network consists of both x and y component of vehicle velocity.

Vehicle tracking is a task that keeps track of road conditions. This allows useful data for applications of reducing accidents on the road. Performance of vehicle tracking system depends on the ability of vehicle detection. This work presents vehicle tracking system that utilizes vehicle features from principal component analysis together with Gabor filter. These vehicle features are examined by the adaptive resonance theory network to recognize and keep track of each vehicle separately without any supervised training. The system is then suitable for tracking vehicle in dynamic environment where the size and view of vehicle are changing in every frame.

2 Vehicle Tracking System

The proposed vehicle tracking system is mainly composed of two parts: vehicle detection and vehicle tracking as can be seen in Fig.1.



(a) (b)

Fig. 1 (a) Vehicle detection system diagram (b) vehicle tracking system diagram

2.1 Vehicle Detection

Vehicles in the image are searched and located using relationship between vehicle size and distance from the camera [5] as given by

$$y_i = \frac{h_i y_c}{v_i - v_0} \qquad (1)$$

where y_i is a vehicle height, h_i is a number of pixels of vehicle in the image, y_c is a camera height, v_i is the last row of vehicle's pixels in the image and v_0 is a vanish line. The system starts searching for vehicles at the vanishing line. The resulting location of vehicle is then used in the vehicle tracking system.

2.2 Vehicle Tracking

The main objective of the vehicle tracking system is to continuously locate each vehicle in the sequence of images. The problem rises when the vehicles are moving because they appear differently in sizes and views at different time frame. The system must be capable of dynamic tracking of vehicle. In this work, the vehicle tracking system consists of two parts: vehicle feature extraction and vehicle tracking (see Fig. 1b). For vehicle feature extraction, the vehicle image is filtered by log-Gabor filter. Next, the principal component analysis (PCA) of the filtered image is computed. The resulting feature vector is then examined by the adaptive resonance theory network.

The log-Gabor filter used in this work can be calculated from the following equation [6].

$$G(w) = \exp\left(\frac{-\log(w/w_0)^2}{2\log(k/w_0)^2}\right) \qquad (2)$$

where w_0 is the filter's center frequency and k/w_0 is constant shape ratio filter. Fig.2 displays an example of log-Gabor filtered image.

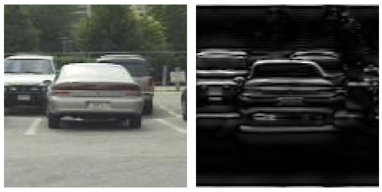
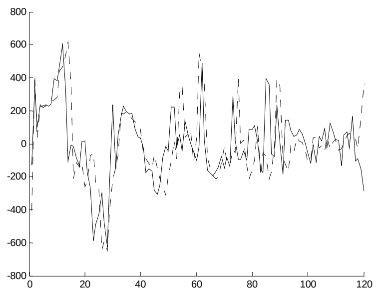


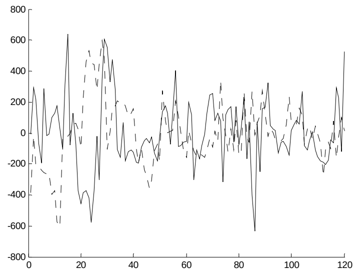
Fig. 2 An example of the log-Gabor filtered image

Resulting of filtered image is transformed by PCA to reduce size of the image. This PCA transformed vector, called vehicle feature vector, of the vehicle in consecutive images can be considered very similar as can be seen in Fig. 3. These vehicle feature vectors are then examined by adaptive resonance theory network to identify and track each vehicle frame by frame.

The network used in this work is ART-2 [7]. Its structure has two main layers: input layer F1 and weight layer F2 (see Fig. 4). The vehicle feature vector is created and stored in the weight layer. The new vector from the next frame is compared to check for the similarity with the weights in the network. If it is sufficiently similar to one of the weight in the memory, it can be recognized as the same vehicle from the previous frame. The corresponding weight is then updated. This implies that the size and view of vehicle are also updated. The number of weights in the network memory indicates number of vehicles being tracked



(a)



(b)

Fig. 3 (a) vehicle feature vectors of the same vehicle of the consecutive frames (b) vehicle feature vectors of different vehicle

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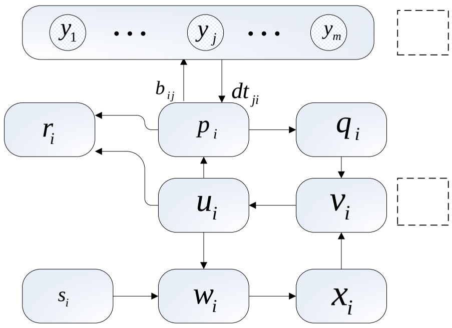


Fig. 4 ART-2 structure

The values of initial weights for tracking vehicles are given by

$$b_{ij}(0) \le \frac{1}{(1-d)\sqrt{n}} \quad (3)$$

$$t_{ji}(0) = 0 \quad (4)$$

The weight is update using the competition learning scheme. Only the winning weight can get updated by the following equations. The winning weight is the maximum y_i. The value of r_i is used for comparing whether or not the new vehicle feature vector is the same vehicle in the network memory.

$$y_j = \sum_i b_{ij} p_i \quad (5)$$

$$r_i = \frac{u_i + cp_i}{\|u\| + c\|p\|} \quad (6)$$

The value of r_i is compared with the vigilance value ρ. If the condition $\|r_i\| > \rho$ is true, the vehicle feature input vector is the same class with the weight being compared, i.e. it is the same vehicle being tracked. The corresponding weight will be updated using the following equation. Otherwise, the network will create new group to represent the new vehicle in the image.

$$t_{Ji} = \frac{1}{1-d} u_i \quad (7)$$

$$b_{iJ} = \frac{1}{1-d} u_i \quad (8)$$

where all constant a, b, c, d, and θ is obtained from [7].

3 Experimental Results

The proposed system has been tested with the image of size 640x480 pixels. The camera is installed in the car at 1.2 meter height. The ART network shows desirable performance in tracking of vehicles. Examples of the tracking are shown in Fig. 5 with percent of accuracy over 90 %. The percent accuracy is computed from the sequence of 610 testing images. Note that the network is not required to track only frontal view of the vehicle as can be seen in Fig.6. The results also demonstrate the capability of simultaneously tracking multiple vehicles.

Vehicle/Views	# of Frames	Missed Tracking	%Accuracy
One vehicle/front and back	760	42	94.45
Two vehicle/front	610	55	90.98
Two vehicle/Different	430	37	91.39

Table 1 Percent accuracy of vehicle tracking

Frame 1 Frame 25

Frame 35 Frame 55

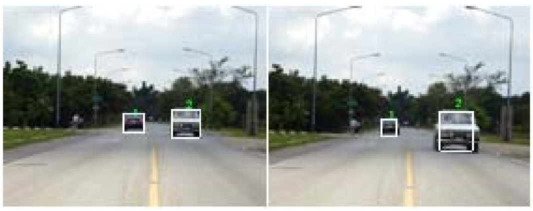
Frame 70 Frame 85

Frame 105 Frame 120

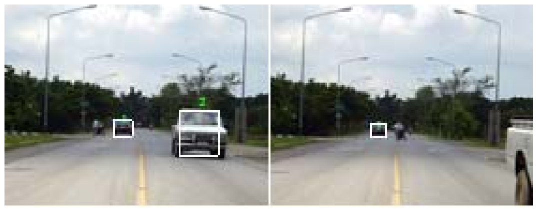
Frame 135 Frame 160

Fig. 5 Examples of frontal vehicle detection

Frame 1 Frame 30



Frame 60 Frame 94



Frame 105 Frame 155

Frame 165 Frame 180

Fig. 6 Examples of detecting different views of vehicle

4 Conclusion

The vehicle tracking system has been proposed by using adaptive resonance theory network to recognize the principal component analysis of the vehicle image. Desirable results have been achieved at percent accuracy over 90%. The false detection of vehicles mainly comes from the vehicle detection system. This part of the system can be further improved to overcome this shortcoming. This work, however, has presented the use of unsupervised ART network to track vehicle with the performance that is sufficient to implement in practical system.

References:

[1] J. van Leuven, M.B. van Leeuwen, and F.C.A. Groen, Real-Time Vehicle Tracking in Image Sequences, *In Proceedings of IEEE Instrumentation and Measurement Technology Conf.*, Budapest, May 21-23, 2001, pp. 2049-2054.

[2] K. She, G. Bebis, H. Gu, and R. Miller, Vehicle Tracking Using On-Line Fusion of Color and Shape Features, *IEEE International Conference on Intelligent Transportation Systems*, Washington, DC, October 3-6, 2004, pp. 731-736.

[3] L. Xie, G. Zhu, Y. Wang, H. XU and Z. Zhang, Real-time Vehicles Tracking Based on Kalman Filter in a Video-based ITS, *IEEE International Conference on Communications, Circuits and Systems*, 2005, pp. 883-886.

[4] A. Bevilacqua, L. Di Stefano, and S. Vaccari., Occlusion. Robust Vehicle Tracking based on SOM (Self-Organizing. Map), *Proceedings of the IEEE Workshop on Motion and Video Computing (WACV/MOTION'05)*, Vol.2, 2005, pp. 84- 89

[5] D. Hoiem, A.A Efros and M Hebert, Putting Objects in Perspective, Computer Vision and Pattern Recognition, *IEEE Computer Society Conference*, Vol.2, 2006, pp. 2137-2144

[6] D. J. Field, Relations Between The Statistics Of Natural Images and The Response Properties of Cortical Cells, *Journal of The Optical Society of America A*, 1987, pp. 2379-2394.

[7] Carpenter, G.A., Grossberg, S., Rosen, ART 2-A: An Adaptive Resonance Algorithm. for Rapid Category Learning and Recognition, *IEEE*, 1991, pp. 493-504.