Anomaly Detection in Vehicle Traffic with Image Processing and Machine Learning

Selim S. Sarikan[a], A. Murat Ozbayoglu[b]

[a]Aselsan A.S. 06172, Ankara Turkey
[b]TOBB University of Economics and Technology, 06560 Ankara Turkey

Abstract

Anomaly detection is an important part of an Intelligent Transportation System. In this study, image processing and machine learning techniques are used to detect anomalies in vehicle movements. These anomalies include standing and traveling in reverse direction. Images are captured using CCTV cameras from front and rear side of the vehicle. This capability makes the results robust to the variations in operational and environmental conditions. Multiple consecutive frames are acquired for motion detection. Features such as edges and license plate corner locations are extracted for tracking purposes. Direction of the traffic flow is obtained from the trained classifier. K-nearest neighbor is chosen as the classifier model. The proposed method is evaluated on a public highway and promising detection results are achieved.

Keywords: Computational Intelligence; Image Processing; Intelligent Transportation Systems

1. Introduction

Anomaly detection is such an important problem that many Intelligent Transportation Systems (ITS) are facing with it. Detecting anomalies in vehicles direction of movement is a subset of this complex problem. Vehicles moving in the wrong direction pose a major risk for other drivers. Without doubt, if anomalies in vehicles direction of movement are detected accurately in real-time; risk of accidents can be decreased significantly.

As the cities and transportation system evolve around smarter and more intelligent counterparts, surveillance systems become an essential issue. Many parameters contribute to build a surveillance system and traffic flow detection is one of the building blocks. There have been many approaches for a reliable detection system.

Traditional methods that employ road sensors are widely used. Sensors buried beneath the road surface may not provide accurate results in case of congested lanes. Additionally, these sensors performance tend to degrade over time. On the other hand, image processing based solutions are more reliable with the advantage of increased compatibility and ease of maintenance.

In the past few decades, studies are made to find a solution to vehicle flow detection problem. Prati et al. (2001) presented a study with shadow detection to reduce classification errors.

In summary, many solutions to unresolved problems exist in vehicle flow detection. In case of dedicated lanes, it is easier to detect and process vehicles rather than free flowing traffic which require more accurate estimation. Additionally, dedicated lanes have slower cruising speeds compared to free flow, which improves sampling performance.

In this paper, a novel vehicle flow detection method is presented. Light curtain information is used to detect vehicles through dedicated lanes. CCTV cameras are utilized to capture images of the vehicle from both ends. By combining image processing with machine learning techniques, each vehicles direction of flow is calculated.

The rest of the paper is organized as follows. Section 2 describes our vehicle flow detection method. Section 3 provides experimental results and discussion of the results. Finally, conclusions and future work are given in Section 4.

2. Vehicle flow detection scheme

Vehicle flow detection consists of three phases: data collection, feature extraction and learning. In this section each of the phases are given in detail. Overall system diagram is given in Fig.1.
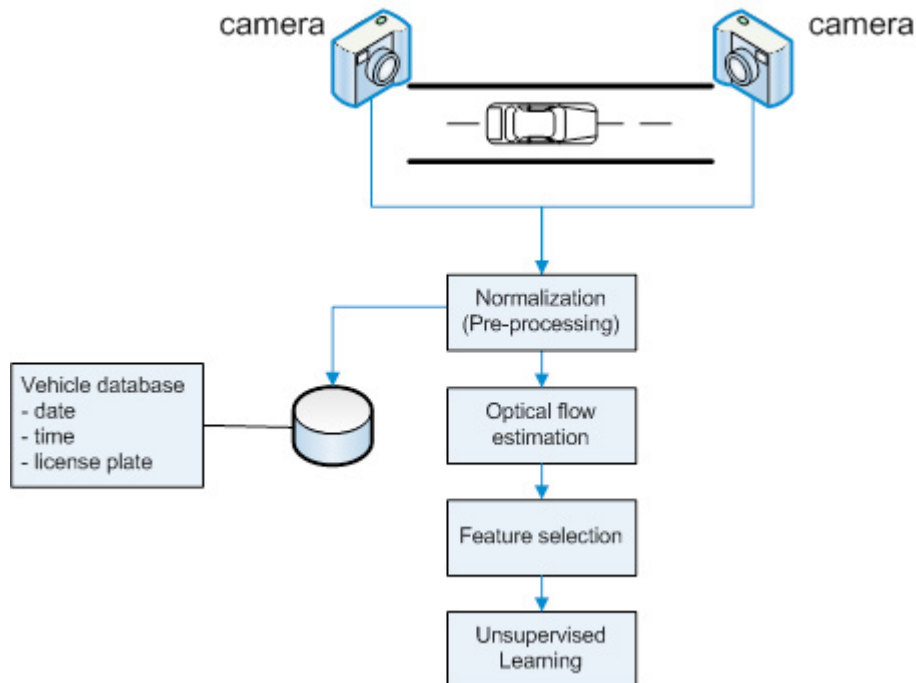

Fig. 1. Vehicle flow detection states

2.1. Data collection

Data is collected from a public motorway. Upcoming traffic is divided into multiple dedicated lanes; each lane is equipped with its own cameras. Installation overview is given in Fig.2. For every vehicle, multiple consecutive frames are recorded for optical flow estimation. Having the flexibility advantage, vision based systems have to adapt varying light conditions. In order to achieve this adaptation property, a light meter is used. Because of variations in the intensity of light, a normalization operation is performed after image acquisition. During night time IR illumination is used.
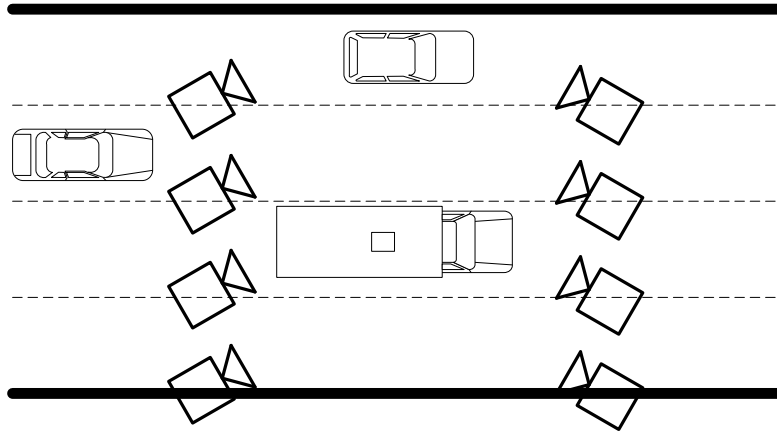

Fig. 2. Data collection setup

Vehicle movements are recorded by multiple cameras to avoid occlusions. Occlusion is an unwanted situation when the region of interest is blocked or masked by another object. Images taken by multiple cameras are given in Fig. 3. Optical flow information along with date, time and license plate is used to generate a vehicle database for training and test purposes. In the next subsection, feature extraction process from this database is given in detail.
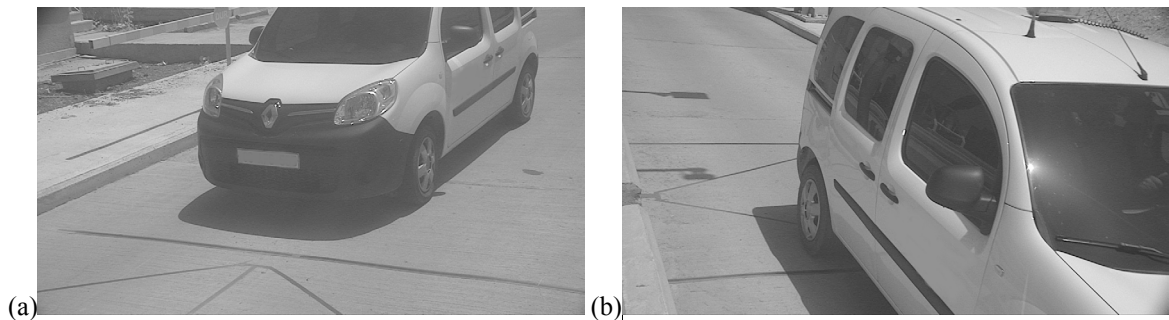

Fig. 3. Roadside images (a) forward movement (b) reverse movement

2.2. Feature extraction

After acquisition of multiple consecutive frames, optical flow algorithm is performed on these set of images. For this purpose Lucas-Kanade pyramidal method in OpenCV is used. Locations with high detail such as licence plate edges and front grill are selected for tracking. After performing optical flow, feature selection is performed in two phases. In the first step, a filtering operation is applied to eliminate unnecessary motion vectors. Since all of the parts of a vehicle are moving together, motion vectors of these parts have to be consistent. With this information known, outliers are discarded. At the second stage, magnitudes of motion vectors are processed to remove irrelevant

motion other than the vehicle of interest.

Optical flow information is combined to generate a single motion vector showing the direction of flow. An example is given in Fig. 4.

Fig. 4. Resultant motion (red line) and feature locations (blue dots)

2.3. Unsupervised learning

After acquisition and optical flow estimation phases, a system with learning ability is designed. Among the very well known types of learning types, unsupervised learning is preferred. Compared to supervised learning methods, unsupervised learning can work with data itself only and does not require any labels assigned. Labeling is an intensive and time-consuming step for a machine learning application. Flexibility is a desired property and by eliminating labeling this goal is achieved. On the other hand, unsupervised learning requires a larger training set to avoid overfitting.

Direction of traffic along the road is determined during this learning phase, besides region of interest is found to mask out redundant scene locations. By eliminating redundant locations overall performance is increased. Frequent locations of the vehicles along the road surface are shown in Fig. 5. Any information outside the red zone is discarded.
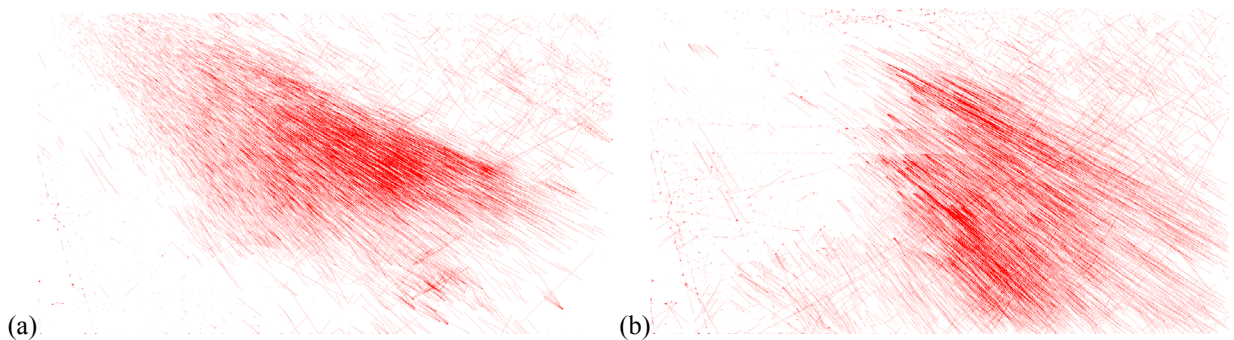

(a) (b)

Fig. 5. Road surface from frequent vehicles (a) 1st camera (b) 2nd camera

3. Experiments and results

To evaluate the performance of the detection scheme proposed, vehicle flow detection software is implemented. The experimental platform is built on OpenCV, C++ and Java. Each vehicle in the test set is compared against training results to find similarities. K-nearest neighbor machine learning method is used to obtain results. Experiments are performed on a computer with 1.73GHz CPU and 8GB RAM.

Although *KNN* is a supervised type of non-parametric method used for classification, *KNN* is used to find the direction of traffic. Since most of the vehicles are traveling in the right direction, majority of the vehicles will group together to form a cluster representing forward direction. On the other hand, reverse moving and other irrelevant movement will form smaller clusters. As a result of this k parameter is selected as 3.

Quadrant number is used for direction labeling. As seen from Fig. 6, motion vectors located in 2nd quadrant belongs to forward moving vehicles, whereas vectors related to reverse motion are located in the 4th quadrant.

Table 1. Training set properties

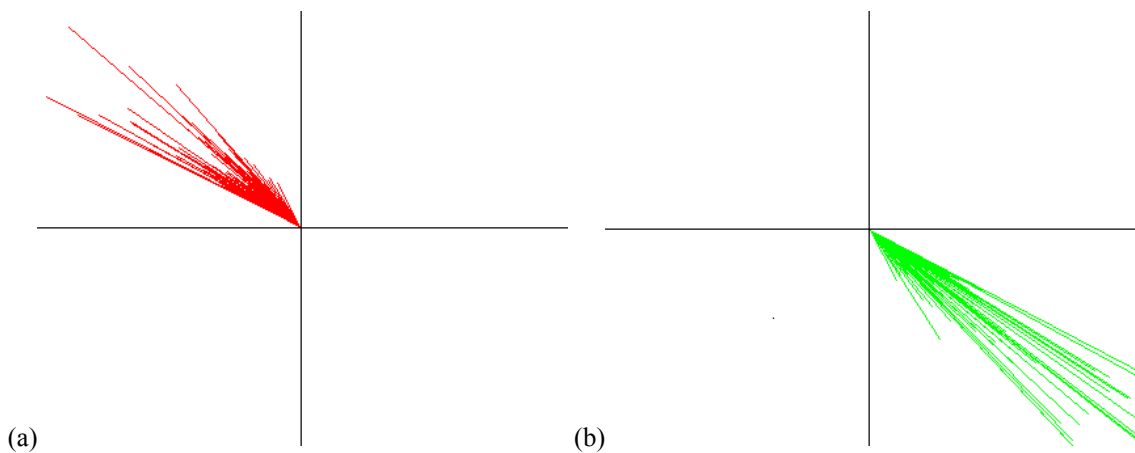|	set size
forward motion	3360
reverse motion	3510

Fig. 6. Motion vectors (a) forward (b) reverse

For testing purposes random vehicles are selected; output of the detection is shown in Fig. 7. Each vehicles direction of flow is detected without any error.
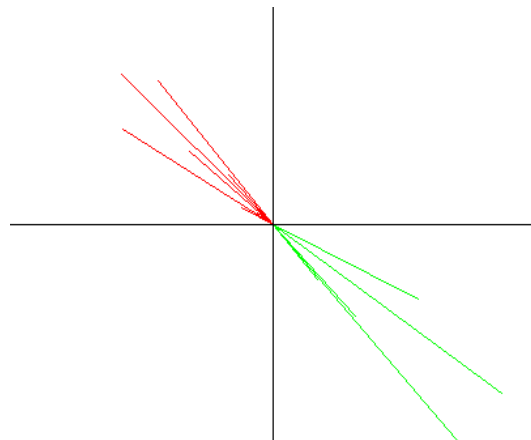

Fig. 7. Test set results, forward (red line) and reverse (green line) movement

4. Conclusion and future work

In this study, a vehicle flow detection approach to distinguish traffic anomalies is presented. Optical flow estimation is performed to detect motion. Moreover, machine learning technique k-nearest neighbor is adapted for unsupervised learning. Different illumination levels during daytime and nighttime are observed. Varying range of vehicles including motorcycles, cars, trucks and buses are detected.

The results from public motorway tests showed that proposed detection method can detect vehicles traveling opposite the traffic flow. This information can be used to notify traffic operators in real time. However, the proposed method requires dedicated cameras to each lane. As an extension, this method can be extended to work with a single camera covering entire road surface.

From machine learning point of view, feature selection and feature extraction still remains as the most important issue. Selected features affect overall accuracy significantly.

In this study, following future research subjects are possible: (1) detection via single camera will be studied; (2) detection of different types of anomalies (stalled, rollover, accident); (3) the detection of humans passing by (non-vehicle entries).

References

[1] X. Pan, Y. Guo and A. Men, "Traffic Surveillance System for Vehicle Flow Detection," 2010 Second International Conference on Computer Modeling and Simulation, Sanya, Hainan, 2010, pp. 314-318.
[2] A. Prati, I. Mikic, C. Grana and M. M. Trivedi, "Shadow detection algorithms for traffic flow analysis: a comparative study," ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No.01TH8585), Oakland, CA, 2001, pp. 340-345.
[3] Duda, R. and Hart, P. (1973) Pattern Classification and Scene Analysis. John Wiley and Sons, New York.
[4] http://opencv.org/, OpenCV library, 29 May 2018
[5] X. Z. Chen, K. K. Liao, Y. L. Chen, C. W. Yu and C. Wang, "A vision-based nighttime surrounding vehicle detection system," 2018 7th International Symposium on Next Generation Electronics (ISNE), Taipei, Taiwan, 2018, pp. 1-3.
[6] L. Herle and P. Sharma, "Vehicle detection and identification in an unconstrained environment," 2017 International Conference on Recent Innovations in Signal processing and Embedded Systems (RISE), Bhopal, 2017, pp. 66-69.
[7] A. V. Vinuchandran and R. Shanmughasundaram, "A real-time lane departure warning and vehicle detection system using monoscopic camera," 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), Kannur, 2017, pp. 1565-1569.
[8] S. Kul, S. Eken and A. Sayar, "A concise review on vehicle detection and classification," 2017 International Conference on Engineering and Technology (ICET), Antalya, 2017, pp. 1-4.
[9] Z. Guo, Z. Zhou and X. Sun, "Vehicle detection and tracking based on optical field," 2017 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC), Shenzhen, 2017, pp. 626-630.
[10] Y. W. Choi, Y. S. Chung, S. I. Lee and S. G. Lee, "Rear object detection method based on optical flow and vehicle information for moving vehicle," 2017 Ninth International Conference on Ubiquitous and Future Networks (ICUFN), Milan, 2017, pp. 203-205.
[11] P. K. Bhaskar, S. P. Yong and L. T. Jung, "Enhanced and effective parallel optical flow method for vehicle detection and tracking," 2015 International Symposium on Mathematical Sciences and Computing Research (iSMSC), Ipon, 2015, pp. 138-143.
[12] Yanfeng Chen and Q. Wu, "Moving vehicle detection based on optical flow estimation of edge," 2015 11th International Conference on Natural Computation (ICNC), Zhangjiajie, 2015, pp. 754-758.
[13] A. M. Jain and N. Tiwari, "Airborne vehicle detection with wrong-way drivers based on optical flow," 2015 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), Coimbatore, 2015, pp. 1-4.
[14] Chen Zhenxue, Wang Guoyou and Liu Chenyun, "Vehicle flow detection statistic algorithm based on optical flow," Proceedings of the Fifth IEEE International Symposium on Signal Processing and Information Technology, 2005., Athens, 2005, pp. 264-268.
[15] K. Noor et al., "Performance analysis of a surveillance system to detect and track vehicles using Haar cascaded classifiers and optical flow method," 2017 12th IEEE Conference on Industrial Electronics and Applications (ICIEA), Siem Reap, 2017, pp. 258-263.
[16] L. Gao, W. Liu, R. Niu, Y. Sun, Y. Xin and H. Liang, "Moving vehicle detection in dynamical scene using vector quantization," 2014 IEEE Intelligent Vehicles Symposium Proceedings, Dearborn, MI, 2014, pp. 725-729.
[17] Z. Silar and M. Dobrovolny, "Utilization of Directional Properties of Optical Flow for Railway Crossing Occupancy Monitoring," 2013 International Conference on IT Convergence and Security (ICITCS), Macao, 2013, pp. 1-4.
[18] K. Kiratiratanapruk and S. Siddhichai, "Practical application for vision-based traffic monitoring system," 2009 6th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, Pattaya, Chonburi, 2009, pp. 1138-1141.
[19] Meng Liu, Chengdong Wu and Yunzhou Zhang, "Multi-resolution optical flow tracking algorithm based on multi-scale Harris corner points feature," 2008 Chinese Control and Decision Conference, Yantai, Shandong, 2008, pp. 5287-5291.
[20] X. Qimin, L. Xu, W. Mingming, L. Bin and S. Xianghui, "A methodology of vehicle speed estimation based on optical flow," Proceedings of 2014 IEEE International Conference on Service Operations and Logistics, and Informatics, Qingdao, 2014, pp. 33-37.
[21] Lucas, B. D. and Kanade, T. (1981). An iterative image registration technique with an application in stereo vision. In Seventh International Joint Conference on Artificial Intelligence (IJCAI-81), pages 674–679, Vancouver.