Speed Identification of Manifold Moving Entities by a Dynamic UAV framework

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Abstract: Speed identification with a visual camera of a moving item has always been a key area in computer vision research. A speed identification system has been introduced in this paper for several moving entities from an on-air platform on the surface by implementing Convolutional neural network.

Keywords: speed monitoring, convolution neural network, optical camera, moving object

INTRODUCTION

Actual-time traffic surveillance is a difficult job. Even with all the finest techniques we have, we are still dealing with inadequate highway data to fix congestion issues. Traffic surveillance systems have developed to more automatic and intelligent. Traffic tracking schemes are flexible, vehicle tracking is automated and the assessment of vehicle density on the highway is also mechanized[1] –[5]. The brief battery life of the UAVs and the absence of profitable methodologies for detecting and tracking traveling vehicles are the primary considerations that avoid this technology from being commonly used. Precise movements are incredibly difficult to determine when both the framework and the target move at the different variance of speed[5]–[8]. Distinguishing accelerating cars or stationary cars in hazardous locations in real-time will be a life-saving resolution. Another paper [9] discloses about a “Traffic Congestion Investigation System” by Image Processing Closed Circuit Television (CCTV) Camera to monitor vehicle status from a highway traffic picture[10], [11]. Other papers [12]–[15] have introduced an optical stream and neural network fusion vibrant target identification procedure

PROPOSED WORK

The “SSIM index” is very little than 0.5 in a first image, (b) various image amount or (c). The FBIA will then be used for image arrangement. When the “SSIM index” is extra than 0.5, CSRT is used for object tracking. During the monitoring phase, the speed of the cars will be measured from the data collection. Image adjustment method (FBIA) is able to distort the vision; therefore, it is essential to utilize reverse homography to get precise screen images with video frames; thus, it is essential to apply reverse homography to get undistorted video models with data.

RESULTS

Two statistics below present the outcomes of this research. Table 1 provides the outcomes of the identification and Table 2 demonstrates the outcomes of the velocity estimate. The handbook tracking compared with quicker R-CNN identification is presented in table 1. Sample images have been gathered from all three places.

Table 1 Outcomes of the identification

	Manual Count		Faster R-CNN Count		Accuracy	
	Small Vehicle	Large Vehicle	Small Vehicle	Large Vehicle	Small Vehicle	Large Vehicle
Glades Road/441 Intersection	506	2	437	2	86.37%	100%
Bluegrass	38	13	35	12	92.10%	92.30%
Burt Aaronson (Static)	19	0	19	0	100%	-
Burt Aaronson (moving)	39	0	33	0	84.61%	-
Total average					90.77%	96.15%

Table 2 Outcomes of the velocity estimate

	Number of Cars Observed	Average Speed Manually Observed (mph)	Average Speed from the Framework (mph)	Accuracy %	RMSE (mph)
Glades Road/441 Intersection (Static drone)	43	0	0	100%	0
Glades Road/441 Intersection (Static drone)	10	30	30.5	98.33%	1.194
Glades Road/441 Intersection (Static drone)	15	25	26	96%	1.111
Bluegrass (Moving drone)	15	0	0	100%	0
Bluegrass (Moving drone)	5	12	11.5	95.83%	0.604
Burt Aaronson (Moving drone)	19	0	100%	100%	0
Burt Aaronson (Moving drone)	2	25	26	96%	1.044
Average				96.80%	0.564

CONCLUSION

In this study, while automobiles are not relocating, then the proposed framework achieved 100 percent speed accuracy. Moreover, from a stationary platform, the suggested framework accomplished over 96 percent velocity precision (Table 2). The most difficult issue was to calculate the speed of the framework. The implementation of the structure under distinct weather conditions and visual circumstances is also a potential path to be pursued.

REFERENCES

[1] D. Biswas, H. Su, C. Wang, J. Blankenship, and A. Stevanovic, "An automatic car counting system using overfeat framework," *Sensors (Switzerland)*, 2017.

[2] Y. L. Chen, B. F. Wu, H. Y. Huang, and C. J. Fan, "A real-time vision system for nighttime vehicle detection and traffic surveillance," *IEEE Trans. Ind. Electron.*, 2011.

[3] F. Liu, Z. Zeng, and R. Jiang, "A video-based real-time adaptive vehicle-counting system for urban roads," *PLoS One*, 2017.

[4] M. Daigavane and P. Bajaj., "Real Time Vehicle Detection and Counting Method for Unsupervised Traffic Video on Highways," *IJCSNS Int. J. Comput. Sci. Netw. Secur.*, 2010.

[5] P. Jadhav, P. Kelkar, K. Patil, and S. Thorat, "Smart Traffic Control System Using Image Processing," *Int. Res. J. Eng. Technol.*, 2016.

[6] X. Zhao, D. Dawson, W. A. Sarasua, and S. T. Birchfield, "Automated Traffic Surveillance System with Aerial Camera Arrays Imagery: Macroscopic Data Collection with Vehicle Tracking," *J. Comput. Civ. Eng.*, 2017.

[7] Y. Kudo, "Traffic flow measurement system using image processing," *Syst. Comput. Japan*, 1986.

[8] B. Eamthanakul, M. Ketcham, and N. Chumuang, "The Traffic Congestion Investigating System by Image Processing from CCTV Camera," in *2nd Joint International Conference on Digital Arts, Media and Technology 2017: Digital Economy for Sustainable Growth, ICDAMT 2017*, 2017.

[9] M. D'Aloia, M. Rizzi, R. Russo, M. Notarnicola, and L. Pellicani, "A marker-based image processing method for detecting available parking slots from UAVs," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2015.

[10] K. Kaarthik, A. Sridevi, and C. Vivek, "Image processing based intelligent parking

system," in *Proceedings - 2017 IEEE International Conference on Electrical, Instrumentation and Communication Engineering, ICEICE 2017*, 2017, vol. 2017-Decem, pp. 1–4.

[11] N. Hafizi and B. Zabawi, "Parking lot detection using image processing method," *ICL TEEE*, pp. 123–129, 2013.

[12] V. Goel, J. Weng, and P. Poupart, "Unsupervised video object segmentation for deep reinforcement learning," in *Advances in Neural Information Processing Systems*, 2018.

[13] L. Bao, B. Wu, and W. Liu, "CNN in MRF: Video Object Segmentation via Inference in a CNN-Based Higher-Order Spatio-Temporal MRF," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2018.

[14] H. Qin, Z. Zhen, and K. Ma, "Moving object detection based on optical flow and neural network fusion," *Int. J. Intell. Comput. Cybern.*, 2016.

[15] K. Lenac, I. Maurović, and I. Petrović, "Moving objects detection using a thermal Camera and IMU on a vehicle," in *2015 International Conference on Electrical Drives and Power Electronics, EDPE 2015 - Proceedings*, 2015.