Re-ID Technology for V2I based Cooperative Driving Protocol

Junhyek Jang
Mobility Platform Research Center
Korea Electronics Technology Institute
Seongnam, Korea
junjang9327@keti.re.kr

Kitaeg Lim
Mobility Platform Research Center
Korea Electronics Technology Institute
Seongnam, Korea
ktlim@keti.re.kr

Sanghun Yoon
Mobility Platform Research Center
Korea Electronics Technology Institute
Seongnam, Korea
shyoon11@keti.re.kr

Daewon Chae
Mobility Platform Research Center
Korea Electronics Technology Institute
Seongnam, Korea
cdwer098@keti.re.kr

Soohyun Jang
Mobility Platform Research Center
Korea Electronics Technology Institute
Seongnam, Korea
shjang@keti.re.kr

***Abstract*—In recent years, there are collaborative efforts in establishing protocols between autonomous vehicles(AV) and infrastructures to provide safety and traffic efficiency on the road. Majority of recently proposed cooperative protocols are done using vehicle to vehicle(V2V) based cooperative driving protocol where AVs communicate with each other to negotiate its actions. However, V2V based cooperative protocols has its limitations in environments with obstructions such as buildings. To overcome such shortages, our team previously proposed a vehicle to infrastructure(V2I) based cooperative driving protocol using common surveillance cameras. To maximize V2I efficiency, the visible range of surveillance cameras needs to be extended. Our team present a developed re-identification algorithm between multi-cameras that can extend visible range of surveillance cameras and support real-time applications.**

Keywords—V2I, Cooperative Driving, Re-ID

I. Introduction

Current autonomous driving technology is not perfect, and there are some areas that have some room for improvements. One of the areas is establishing a cooperative protocol in between autonomous cars to improve safety and efficiency on the road. In a situation where multiple autonomous vehicles have different intentions, there needs to be a protocol managing which car will perform specific actions to avoid collision.

In the recent efforts by SAE International, the organization released SAE J3216[5], a document establishing cooperative protocols mainly for cars capable of V2V communication. However, V2V based cooperative protocol has its own limitations in situations where there is an obstruction such as buildings in between cars. To complement V2V based cooperative protocol, our team previously proposed a V2I based cooperative autonomous driving protocol.

Our proposed V2I based cooperative driving protocol uses surveillance cameras installed on a road side unit(RSU) to inference and generate key information on the road which includes the speed and the location of each car in the blind spots[2]. The generated information is then transmitted to nearby cars capable of V2I communications for cars to make appropriate actions.

The proposed protocol is tested at a three-legged intersection in Incheon, South Korea, using connected vehicle, normal vehicle, and autonomous vehicle as shown in Fig.1. Three monocular surveillance cameras are installed on a RSU at the intersection each viewing different sections. Two cameras are viewing the main road with different zoom levels, and a camera is viewing the merging road. The images from the cameras are collected and are analyzed to generate key information in the system installed on the RSU. In this paper, the details of algorithms used to generate key information of the road are introduced, including proposed vehicle re-identification algorithm between cameras.

II. Methods for V2I based Cooperative Autonomous Driving

With limited resources, the applied algorithm needs to support real-time operation and reliable performance. In addition, the viewing angles of installed surveillance cameras are prone to occlusions among the cars, and the used algorithms needs to be robust in an environment with frequent occlusions. Our proposed algorithm consists of three parts which are object detection and tracking, autonomous vehicle identification and re-identification, and speed estimation.

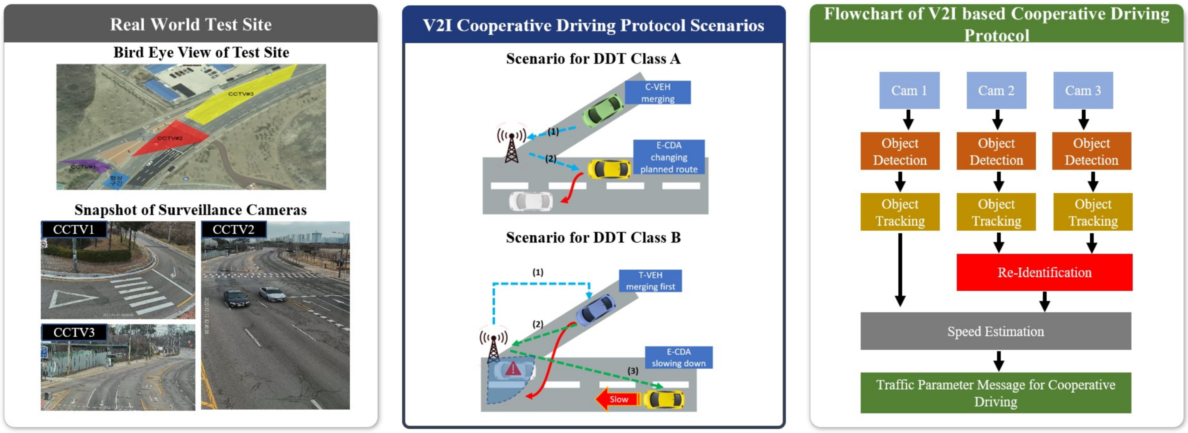

Fig. 1. V2I based Cooperative Driving Protocol Algorithm and Test-site Layout

A. Object Detection and Tracking

In this stage of the algorithm, the cars on the road are recognized and tracked in between frames to inference real-time position and speed of each car. To support real-time application, single stage object detection model, YOLOv5[1], is used to identify various types of cars on the road. Then detected cars are tracked using the StrongSORT[7] algorithm which is capable of tracking objects in real-time and is robust in environment with frequent occlusions.

B. Autonomous Vehicle Identification and Re-ID

In this stage, autonomous vehicle on the road is identified and re-identified in between cameras. The analyzed information of identified autonomous vehicle can be used to alert nearby connected vehicles, and the algorithm can dedicate more computing resources assisting its driving experience. In this paper, we propose a hybrid re-identification algorithm that incorporates deep learning and homography projection to re-identify autonomous vehicle in between cameras.

C. Speed Estimation

In this stage, relevant information such as current speed and estimated time of arrival at the intersection is estimated. Taking advantage of fixed camera angle, the speed of cars is estimated using a homography projection between pixel points and GPS coordinates. In addition, appropriate optimization has been applied to remove random fluctuation and curvature of the road.

III. Proposed Multi-camera Re-Identification

The commonly used surveillance camera only has a visible range of 70m. To extend the visible range, two surveillance cameras viewing different sections of the main road with different magnification powers are installed in our test site. The camera with higher magnification power views the distant section of the road and tracks detected vehicles on the road. The second camera with lesser magnification power views the closer section of the road. Using our proposed re-identification algorithm, the cars detected in the distant range are matched and re-identified with the detected cars in the closer section of the road.

In this paper, our team proposes a hybrid re-identification algorithm that combines homography matching method and CNN based deep learning method. The proposed algorithm is very light and can support real-time applications.

A. Homography based Method

Homography is a linear transform that projects a vector space to another vector space. In digital image processing, the homography transform allows fast conversion of pixel coordinates from one image to another pixel coordinates in another image. In our algorithm, the centroid point of detected cars from the camera viewing the distant area is multiplied with a homography matrix to project the centroid point onto the vector space in camera viewing the closer area. Then centroid distance between projected centroid and detected centroid is calculated to match cars in two images.

The benefit of homography based re-identification algorithm is fast inference time, but it shows its weakness in performance when there are occlusions between the cars. In addition, since the centroid point are the results from the object detection algorithm, the homography based algorithm is heavily dependent on the performance of object detection model.

B. Deep Learning based Method

In our real-time application, a light CNN based model, OSNet[4], is chosen to re-identify cars in between two images. From the commonly used Re-ID algorithms such as ResNet[3] and MobileNet[8], OSNet performed the best with manageable FLOPs using our custom dataset consisting of 19,000 images of 295 different types of cars as shown in Table 1.

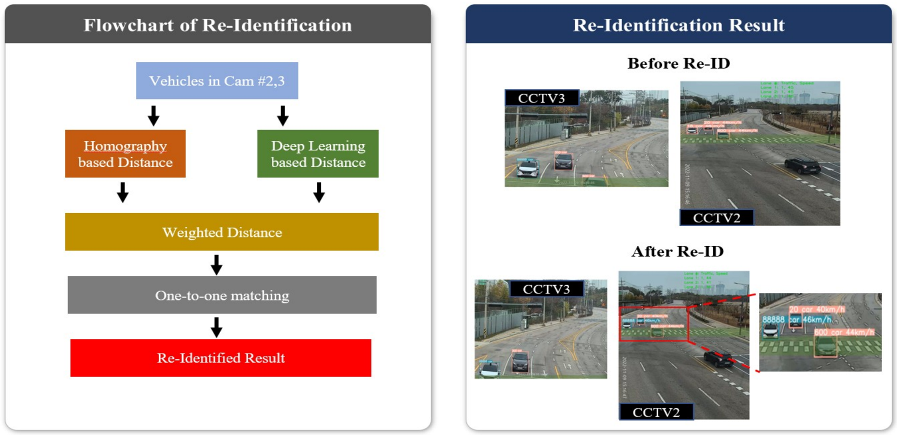

Fig. 2. Re-identification algorithm flowchart and its result

OSNet extracts feature vectors from cropped images of cars and compares feature distance between the extracted feature vectors. OSNet has a fast inference time but shows poor performance when there are cars with similar outer appearance. To improve Re-ID performance, a deep learning model with larger parameter can be chosen. However, with larger model, the real-time inference may not be a viable option depending on GPU.

C. *Proposed Hybrid Method*

Homography based method has a shortage when there is an occlusion between detected cars, and deep learning based method shows weakness when there are cars with similar appearances. To complement shortages in each method, our team propose a re-identification algorithm that combines both methods.

The proposed algorithm initially calculates centroid distance and feature distance using homography and OSNet respectively. Then two distances are added with some weights to output final distance values for objects in two cameras as shown in Fig. 2.

Based on combined distance values, the vehicles in two surveillance cameras are one-to-one matched using the Hungarian algorithm.

TABLE I. PERFORMANCE METRIC FOR RE-ID MODELS

Model	Rank - 1	mAP@0.5	FLOPs
ResNet50[2]	85.5%	70.8%	4,054,319,616
MobileNet[6]	75.0%	57.0%	381,847,424
MLFN[5]	84.0%	64.3%	2,771,421,376
OSNet[3]	89.0%	72.3%	978,878,352

IV. CONCLUSION

In this paper, our team propose a hybrid re-identification algorithm merging homography and deep learning based methods that can support real-time environment. Our proposed algorithm can extend the visible range of widely available surveillance cameras, and can effectively manage autonomous vehicles on the road, particularly in V2I based cooperative driving protocol. In the future, we plan to apply our work on multi-camera re-identification algorithm in other real-time applications that requires extended camera range.

ACKNOWLEDGMENT

This research was supported by the 2021 autonomous driving development innovation project of the Ministry of Science and ICT, 'Development of attack response and intelligent RSU technology for vehicle security threat prevention' (No. 2021-0-01277).

REFERENCES

[1] G. Jocher, A. Chaurasia, A. Stoken, J. Borovec, NanoCode012, Y. Kwon, K. Michael, TaoXie, J. Fang, Imyhxy, Lorna, Yifu, Zeng, C. Wong, A. V, D. Montes, Z. Wang, C. Fati, J. Nadar, Laughing, UnglvKitDe, V. Sonck, Tkianai, yxNONG, P. Skalski, A. Hogan, D. Nair, M. Strobel, and M. Jain, "Ultralytics/yolov5: V7.0 - yolov5 sota realtime instance segmentation," *Zenodo*, 22-Nov-2022. [Online]. Available: https://doi.org/10.5281/zenodo.3908559. [Accessed: 29-Mar-2023].

[2] J. Jang, J. Baek, K. Lim, Y. Ro, S. Yoon, and S. Jang, "A study on V2I based cooperative autonomous driving," 2023 International Conference on Electronics, Information, and Communication (ICEIC), 2023.

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

[4] K. Zhou, Y. Yang, A. Cavallaro, and T. Xiang, "Omni-scale feature learning for person re-identification," 2019 IEEE/CVF International Conference on Computer Vision (ICCV), 2019.

[5] SAE Cooperative Driving Automation (CDA) Committee. "SAE J3216 Taxonomy and Definitions for Terms Related to Cooperative Driving Automation for On-Road Motor Vehicles." SAE International (2020).

[6] X. Chang, T. M. Hospedales, and T. Xiang, "Multi-level factorisation net for person re-identification," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018.

[7] Y. Du, Z. Zhao, Y. Song, Y. Zhao, F. Su, T. Gong, and H. Meng, "Strongsort: Make deepsort great again," *IEEE Transactions on Multimedia*, pp. 1–14, 2023.

[8] Y. Harjoseputro, I. P. Yuda, and K. P. Danukusumo, “MobileNets: Efficient convolutional neural network for identification of protected birds,” International Journal on Advanced Science, Engineering and Information Technology, vol. 10, no. 6, p. 2290, 2020.