Speed Estimation Using Deep Learning with Optical Flow

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***Abstract*—We have tried to estimate the vehicle speed based on the video recorded in a dashcam by using deep learning with optical flow. In the experiments, we used two kinds of optical flows generated by Lucas-Kanade and Gunner-Farnebäck to confirm the effectiveness of optical flow.**

I. Introduction

Vehicle speeds are observed on a highway for surveillance by measuring the time in which a vehicle passes through the specified area [1], tracking the moving objects [2], or using deep learning [3]. Nowadays, a dashcam is very popular and is equipped in almost all cars; however, a low-price dashcam cannot record the speed. It is a very important and challenging issue to estimate car speed based on the video viewed from its car, especially when a traffic accident occurs. The estimation is, however, very difficult especially where no fixed objects exist for the reference, and oncoming and passing cars lead to the error. Some study uses Gyro or acceleration sensors [4], and others utilize deep learning [5].

II. Method

This research employs 3D convolutional networks (3DCN) [6] as the basic learning model, and the learning data are video recorded on a highway in Japan, which speed ranges from 70 km/h to 100 km/h so there are 31 kinds of speeds. At each speed, there are 24 data. Then, 744 (=31×24) data are used in total, and one data has 16 frames to follow the movement. The resolution of the original image is 1,920×1,080, which is reduced to 256×144 for faster learning.

Four-fold cross-validation is used to validate the learning model in this experiment. After 4 learning models are obtained, one final model is generated by using the whole learning data including the training and validation ones. The final model is examined by using 2 new test data at each speed. The final speed is calculated by the weighted average with the probability of each estimated speed. In the experiments, two kinds of methods are used to generate optical flow: Lucas-Kanade [7] and Gunner-Farnebäck [8], which generate coarse and fine optical flows, respectively.

III. Results and Discussion

Fig. 1 shows two kinds of learning and test images: an image without optical flow and one with optical flow. Table 1 shows the results of the experiments, which show that the average error is reduced by using the image with optical flow, while the maximum one becomes larger for the image with optical flow generated by Lucas-Kanade. This was caused by just one mis-estimation that decided the speed 79 km/h as 98 km/h. If this estimation is excluded, the average and maximum errors become 1.4 km/h and 10.0 km/h, respectively, which are shown in parenthesis. This means that optical flow can contribute to reducing both average and maximum errors. On the other hand, both average and maximum errors obtained by using the image with optical flow generated by Gunner-Farnebäck were smaller than those obtained by using Lucas-Kanade.

(a) Image without optical flow **(b) Image with optical flow**

Fig. 1. Two kinds of images used for the experiments.

Table 1. Results of the experiments [km/h]

	Without optical flow	With optical flow	
		Lucas-Kanade	Gunner- Farnebäck
Ave. error	**3.8**	**1.7 (1.4)**	**1.5**
Max. error	**16.0**	**19.0 (10.0)**	**9.0**

Finally, it has been found that the employment of optical flow can contribute to reducing both average and maximum errors, and the fine optical flow generated by Gunner-Farnebäck is more effective in reducing the errors than the coarse one generated by Lucas-Kanade.

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