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**Complementing Vehicle Trajectories
Using Two Camera Viewpoints**

by

Katsuaki Nakano

A Thesis Submitted in Partial Fulfillment of the Requirements for the
Degree of Master of Science in Computer Engineering

School/Department of Computer Engineering
Kate Gleason College of Engineering

Rochester Institute of Technology
Rochester, NY
May 30, 2024

Complementing Vehicle Trajectories Using Two Camera Viewpoints

Katsuaki Nakano

Committee Approval:

Minoru Nakazawa *Advisor* Date
Department of Computer Engineering, Kanazawa Institute of Technology

Michael Zuzak *Advisor* Date
Department of Computer Engineering

Andres Kwasinski Date
Department of Computer Engineering

Dongfang Liu Date
Department of Computer Engineering

Abstract

Traffic volume surveying is a crucial activity to get traffic statistics for road management and traffic congestion control. In recent years, the target environment of traffic volume surveying has become more complex, such as the fully automated surveillance of many-way intersections. Further compounding this complexity, some local governments may not be able to install a camera at a high enough elevation to capture the entire intersection due to environmental, legal, safety, or cost restrictions. Therefore, bigger objects such as buses and trucks often occlude other vehicles in the captured image. This occlusion degrades the accuracy of counting and is one of the main problems that makes the automation of traffic counting at intersections difficult. In this work, I propose a Bird's-Eye View (BEV) transformation method capable of 1) removing camera distortion created by wide-angle cameras installed at lower elevations (a common scenario in traffic volume surveys), and 2) utilizing multiple viewpoints to complement object trajectories to reduce accuracy loss caused by occlusion. Furthermore, I evaluate the effectiveness of the proposed method using real-world traffic survey data collected at an intersection in Japan.

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Chapter 1

Background

1.1 Introduction

In Japan, traffic volume surveys for national roads and streets are conducted once every five years by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) to determine the traffic volume on roads throughout Japan and to provide the traffic statistics for road management planning [1]. Currently, these surveys on local roads are mainly conducted manually. Meanwhile, on roads under the direct control of the MLIT, AI analysis using CCTV camera images and image processing technologies uses constant observation to perform automatic traffic counting. The use of automated traffic counting technologies is expected to further increase because the MLIT discontinued manual observation of local road sections during the fall of 2021 [2]. As a result, the MLIT expects traffic volume surveys on local roads to be fully automated, creating an urgent need for automated survey techniques using sensors and AI. To automate traffic surveys on local roads, measurement by direction in complex environments such as many-way intersections will be required. Intersections present a particular challenge as some local governments may not be able to secure a camera position high enough to capture the entire intersection due to local restrictions. This results in bigger objects such as buses and trucks occluding other vehicles within the captured image. Prior work on automated driving has shown that occlusion makes the automation of object tracking tasks challenging [3].

In this study, the purpose is to develop a counting system that is robust to occlusion and camera distortions. The contributions of the work are summarized as follows:

- I develop a method that uses multiple low-angle camera viewpoints to complement broken trajectories without using appearance features. By doing so, traffic survey accuracy degradation caused by occlusion and camera distortion is reduced. While I apply the proposed method exclusively to a traffic survey scenario, it can be applied to any multi-view, multi-object tracking problem where occlusion limits accuracy.

- I evaluate the proposed methodology by applying it to real-world traffic survey data collected at an intersection in Japan. The proposed method produces a 5.3% improvement in the overall accuracy over prior automated methods that use a single viewpoint.

1.2 Background and Preliminaries

1.2.1 Multi-Object Tracking

Multi-object tracking (MOT) is a crucial task in computer vision that involves tracking multiple objects moving in a video by assigning a unique ID to each of them in each frame. MOT methods are broken down into two categories: Tracking-by-Detection [4,5,6] and One-shot [7,8]. Tracking-by-Detection methods divide the task into two phases: detection and tracking. Tracking-by-Detection has the advantage that we can select a suitable model for each of the detection and tracking tasks. YOLO [4] is a typical detection model for Tracking-by-Detection. For a tracking model, SORT [5] and its extension DeepSORT [6] are representative models. In general, a tracking model processes detection results inferred by a detection model to realize Tracking-by-Detection. Meanwhile, one-shot methods combine detection and tracking in a single model and are generally characterized by faster processing speeds than Tracking-by-Detection methods. FairMOT [7] and JDE [8] are representative one-shot models.

The MOT challenge [9], a person tracking benchmark, uses 20 indicators to evaluate the performance of object tracking models, of which Multiple Object Tracking Accuracy (MOTA) [10] is a measured task effectiveness indicator. However, one-shot methods are often optimized with parameters specific to human tracking in the MOT challenge. In traffic volume surveys, the classes are not limited to people, but also include a wide range of objects such as cars, buses, cyclists, etc. Thus, the proposed system employs Tracking-by-Detection models as tracking models.

1.2.2 Multi-Camera Multi-Target Tracking

Multi-camera multi-target tracking (MTMCT) is another important task in computer vision that aims to detect and track multiple targets in a multi-camera environment. The general pipeline of MTMCT methods is composed of the following two phases: 1) the local trajectory generation phase that tracks and detects target objects to generate a local trajectory for each perspective, and 2) the cross-camera trajectory matching phase that matches a local trajectory across all cameras to generate a complete trajectory within the entire multi-camera network. An important unsolved problem in MTMCT is object occlusion, which leads to incomplete local trajectories within specific cameras that degrade the accuracy of cross-camera trajectory matching [11]. I note that this problem is present in any MOT task, hence, improvements in MOT models contribute to addressing the challenges created by occlusion.

The main challenge addressed by MTMCT is the considerable variations in visual appearance between different perspectives from different cameras. Several works have explored methods to overcome these differences in appearance between camera perspectives [12,13]. Hu et al. uses epipolar geometry to calculate the correspondence between all cameras [12]. To do so, the authors project lines and detected object coordinates into a reference plane to find the correspondence. Xu et al. uses a Hierarchical Composition of Tracklet (HCT) to match local trajectories by considering multiple cues of objects such as their visual appearance and coordinates on the ground plane [13].



Fig. 1. A Viewpoint in AI City Challenge Dataset [13]

Typical datasets for evaluating MTMCT algorithms include the AI City Challenge [14] and the Duke-MTMC dataset [15]. In such datasets, the Region of Interest (ROI), surrounded by blue lines in Figure 1, and the Motion of Interest (MOI), represented by red arrows in Figure 1, are set. Vehicles are often counted according to these identifiers. In some cases, such as the AI City Challenge camera viewpoint shown in Figure 1, the camera is positioned higher than the traffic signal, making occlusion unlikely. As a result, existing methods are likely not designed to handle occlusion, limiting their applicability to intersections with height restrictions, where occlusion is common. In addition, methods that use appearance features have the problem of producing different matching results when the differences in appearance features between different cameras are too large, or when distinct objects are visually similar. Therefore, in this study, I propose a method to complement broken trajectories without appearance features by using camera calibration and homography matrices for Bird's-Eye View (BEV) transformation that is applicable to wide angle cameras located in low elevation positions.

Chapter 2

Method

2.1 Overview of Proposed Method

The proposed method converts vehicle trajectories obtained from two camera perspectives into BEV images. Then, it detects a situation where the vehicle trajectory is broken in one perspective but is correctly tracked for a longer period in the other perspective. This scenario indicates that occlusion has occurred in the intersection, causing an object detection to drop in the occluded perspective, while remaining present in the other non-occluded perspective. By doing so, trajectories can be maintained as long as at least one camera retains its detection of the target. This allows existing MCMT systems to overcome accuracy loss caused by occlusion events.

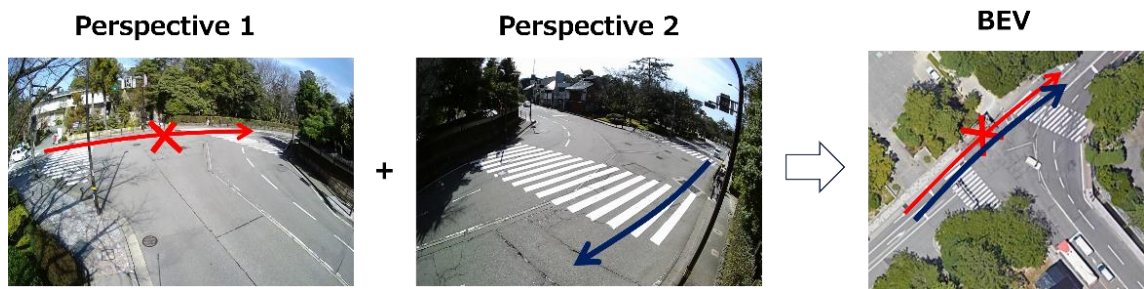


Fig. 2. The Overview of Proposed Method

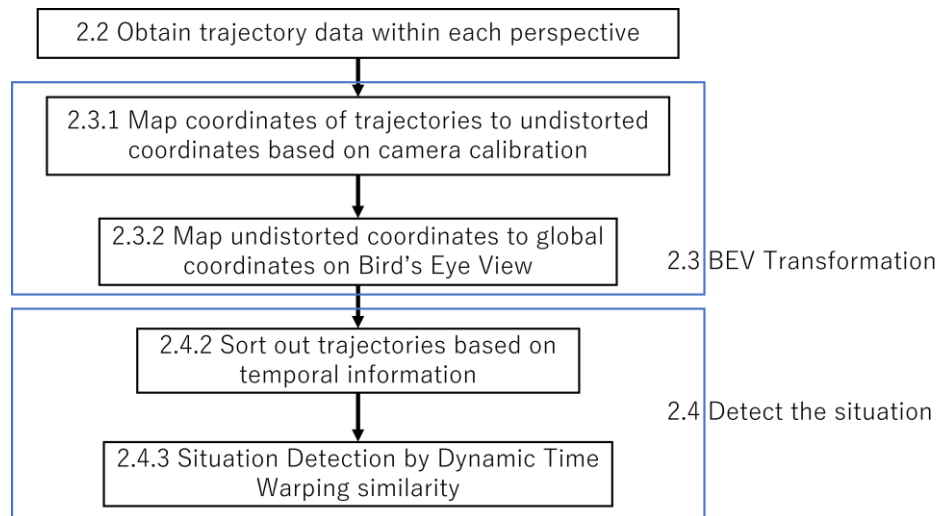


Fig. 3. Chart of the Proposed Method

Figure 2 shows an example of an occluded trajectory being recovered with the proposed method. In this example, the red trajectory in perspective 1 and the blue trajectory in perspective 2 show the same object passing through at the same time. However, notice that in perspective 1, the object IDs are switched in the middle of the trajectory. Throughout the process shown in Figure 3, the trajectories of these two different viewpoints are mapped into BEV, and the Dynamic Time Warping (DTW) similarity of the trajectories is used to detect situations where one trajectory is interrupted while the other trajectory is being tracked correctly (i.e., occlusion). Similarly, an interruption in perspective 2 can be recovered using perspective 1 in the same way, thereby reducing the overall number of broken trajectories, and improving MCMT tasks, such as vehicle counting.

2.2 Generating Local Trajectories

To generate local trajectories for each perspective, we utilize an MOT algorithm called StrongSORT [16]. StrongSORT follows a Tracking-by-Detection approach, using YOLO as the detection phase and a tracking module that is extended from DeepSORT [6]. The major improvement over DeepSORT is AFLink which enables the model to perform global linking without using visual appearance. Figure 4 shows an example of tracking results.



Fig. 4. Trajectories obtained by StrongSORT

2.3 Trajectory Mapping to BEV

2.3.1 Camera Calibration

If a wide-angle camera image is input as-is for overhead view conversion, a distorted overhead view is obtained. This will result in a distorted image when converted to BEV, where objects near the edges of the image will appear to be curved. To resolve this, a more accurate bird's-eye view conversion requires distortion correction by camera calibration.

Camera calibration is a technique for correcting images by determining internal camera parameters such as lens focal length, camera position, and camera orientation. Calibration was performed using OpenCV functions. The input data for obtaining the internal parameters is the chessboard shown in Figure 4. These images are taken with a wide-angle camera from various angles and distances. A total of 40 of these boards were input for parameter estimation. The `findChessBoardCorners` function in OpenCV is input-sensitive, and the corner detection may not work correctly depending on the light conditions, so the contrast value of the input images was set high.

The Figure 6 shows the result of the distortion correction using the camera's internal parameters obtained from the camera calibration.



Fig. 5. An Input Image for Calibration

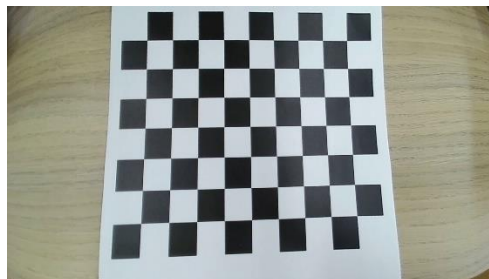


Fig. 6. Undistorted Image

2.3.2 BEV Mapping by Homography Matrix

The homography matrix is a 3×3 matrix of projections for the planes in 3D space. The format of this matrix is in Equation (1). The homography matrix can be obtained using OpenCV's findHomography function.

$$H = \begin{pmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{pmatrix} \quad (1)$$

$$x' = \frac{M_{11}x + M_{12}y + M_{13}}{M_{31}x + M_{32}y + M_{33}} \quad (2)$$

$$y' = \frac{M_{21}x + M_{22}y + M_{23}}{M_{31}x + M_{32}y + M_{33}} \quad (3)$$

To obtain the homography matrix, it is necessary to input four or more corresponding coordinates of the image to be converted to overhead coordinates and the BEV image. Then, the coordinates x and y of each pixel are transformed to x' and y' in equations (2) and (3) based on the homography matrix parameters obtained. The four red dots in the Figure 7 and 8 depict the corresponding points overlaid onto each image.



Fig. 7. Corresponding Points in Perspective 1

The Figure 9 is the result of the transformation based on the corresponding points. Compared to Figure 10 without distortion correction, the distortion of the crosswalk in the upper right corner of the image, which is curved toward the back, has been corrected, resulting in a more accurate transformation result.

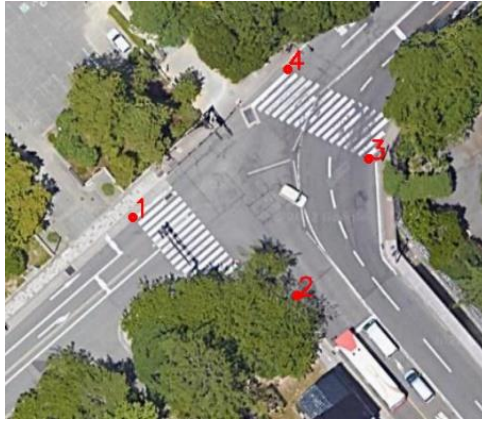


Fig. 8. Corresponding Points in BEV

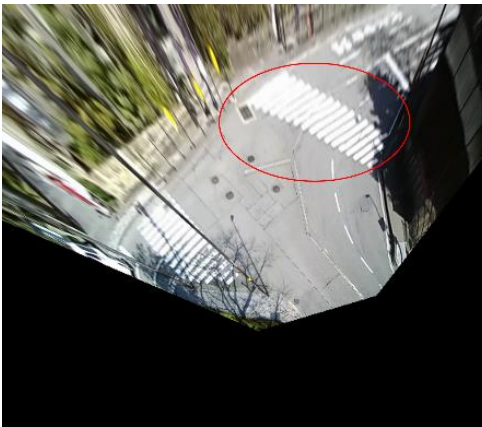


Fig. 9. BEV Transformation Result with Camera Calibration

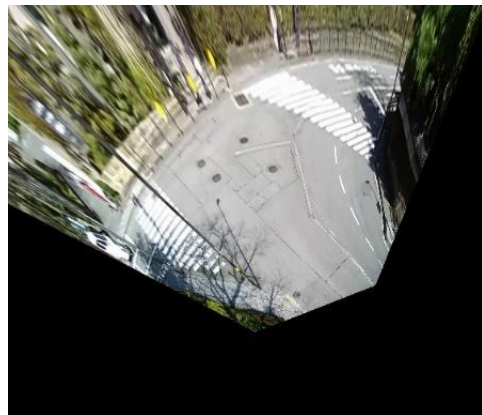


Fig. 10. BEV Transformation Result without Camera Calibration

2.4 Occlusion Scenario Detection

2.4.1 Target Trajectories

To perform traffic counting, each image has a defined region of interest based on the number of entries. An example of a region of interest (ROI) is shown in Figure 11. Traffic counting is performed by counting trajectories that move through the boundaries of this region. Trajectories with a start or end point within the region of interest indicate an interrupted trajectory (e.g., an occlusion event). In prior counting methods, these trajectories are not counted properly because they do not cross the region of interest boundary, degrading counting accuracy.

Therefore, to improve accuracy, trajectories that have their start point within the region of interest must be complemented. Figure 12 shows an example trajectory that is interrupted in the region of interest. The green points are the starting point of the trajectory, and the yellow points are the end point of the trajectory.

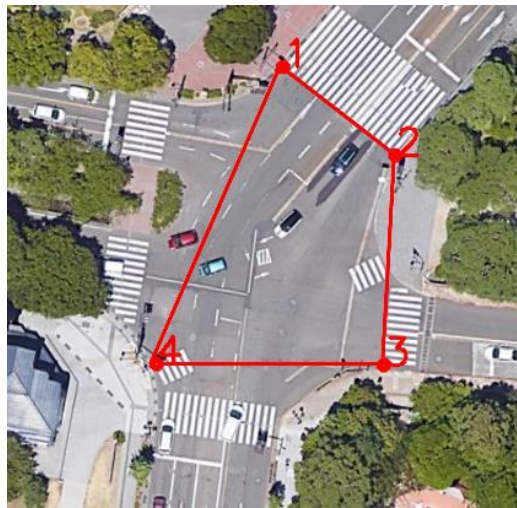


Fig. 11. An Example of ROI

2.4.2 Extracting Similar Trajectories from Another Viewpoint by Temporal Information

For each vehicle trajectory from one viewpoint that exists within the range, candidate similar trajectories from another viewpoint that existed at the same time are selected. Since the manual frame synchronization resulted in a time gap of up to 5 frames, this function extracts all trajectories from the other viewpoint that existed in the 5 frames before and after the frame of interest. Figure 12 shows the extracted trajectory derived from temporal information. The red trajectory is obtained from the perspective 1. The blue trajectories are obtained from the perspective 2 existing in the 5 frames before or after when the red trajectory existed.

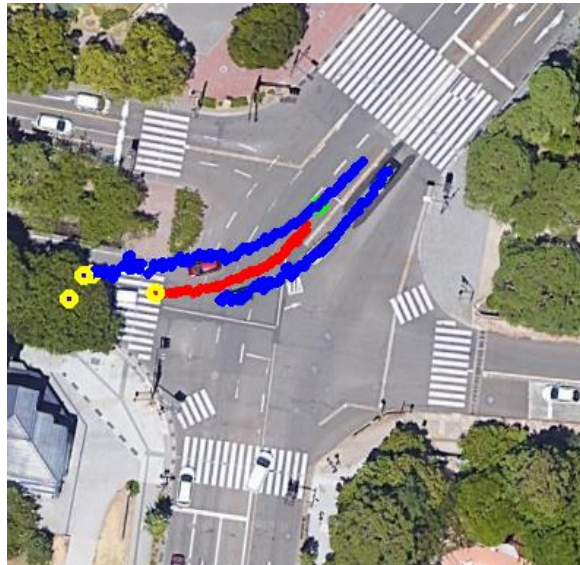


Fig. 12. Trajectories from the Other Perspective Selected by Temporal Information

2.4.3 Selecting the Most Similar Trajectory by Dynamic Time Warping

Dynamic Time Warping (DTW) [16] is a method to measure the distance and similarity between time-series data. DTW can be applied to time-series data of different lengths because it finds the shortest path using a brute-force comparison of distances at each point. To extract the most similar trajectory, DTW is employed for vehicle trajectories using Euclidean distance. The trajectory shown in pink in the Figure 13 is the most similar trajectory to the broken trajectory determined by DTW. Because extremely short trajectories may be selected when evaluating DTW alone, the Euclidean distance between the start and end points of each trajectory is also compared. If the similar trajectory determined by DTW is longer than the target trajectory in red, the pair of trajectories between perspectives is detected as a candidate target to be replaced.

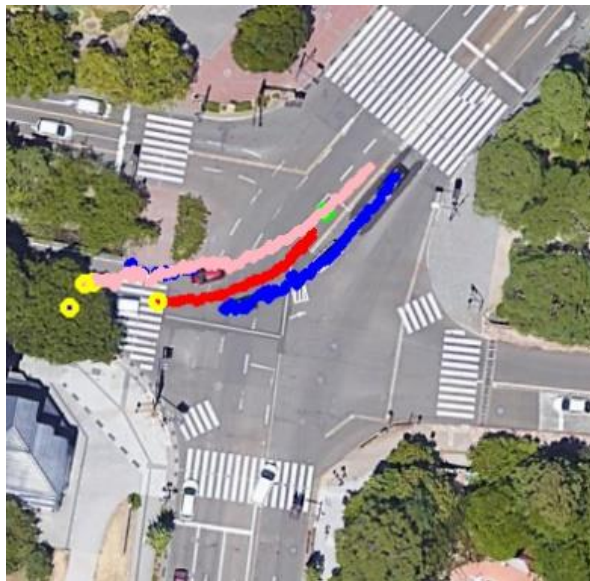


Fig. 13. The Most Similar Trajectory Selected by DTW

Chapter 3

Evaluation

3.1 Target Data

To evaluate the proposed method, it is applied to a multi-viewpoint recording of an intersection in Kenroku, Japan. A bird's-eye view of the evaluation intersection, obtained from Google Earth, is shown in Figure 13. The viewpoint of the two cameras over the evaluation intersection is shown in Table I. As shown in Figure 14, the two viewpoints are set almost diagonally across the intersection. The video used for evaluation was recorded at a height of 4.5m from the ground using a Panasonic HX-A1 with the wide-angle setting enabled. The videos recorded from the two cameras were manually synchronized to ensure that frames from each viewpoint corresponding to the same time instant were processed together.

TABLE I
Kenroku Intersection

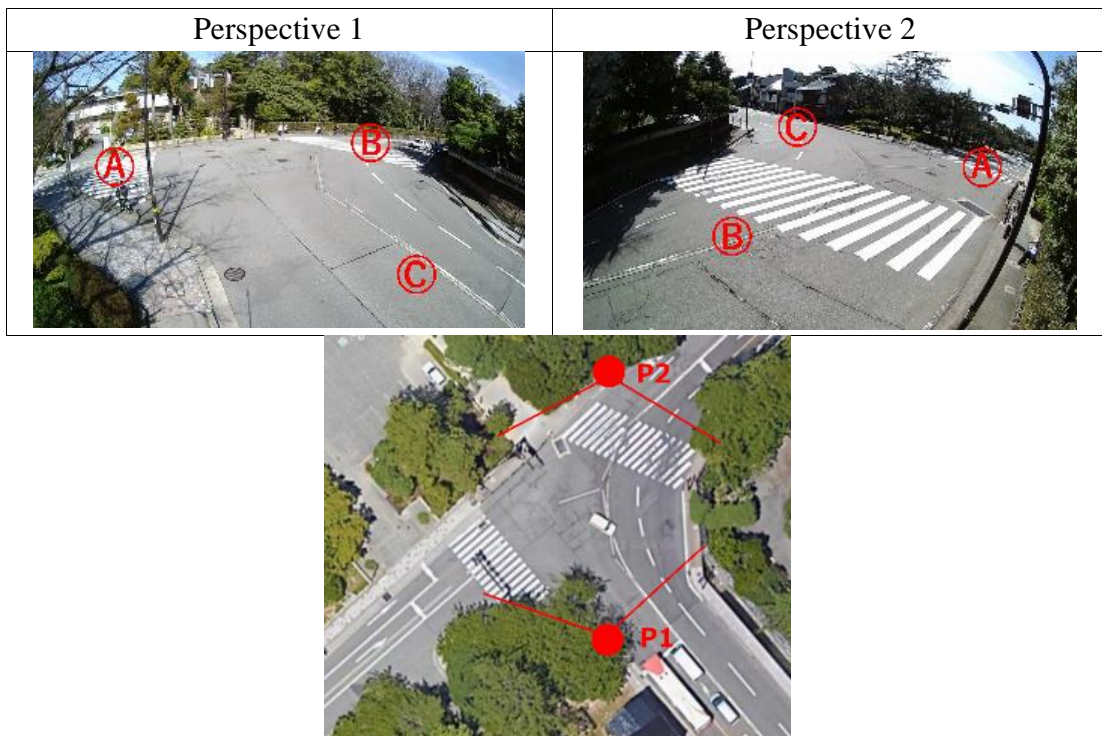


Fig. 14. Camera Installation Points on BEV

3.2 Experimental Methodology

For the evaluation of the proposed method, the result of counting by lines are compared with the result after applying the proposed method. As shown in Figure 16, traffic counting is performed by line for each entry of the intersection. Each line detects vehicles passing through it and stores IDs of the detected vehicles. By comparing IDs stored in each line, we can obtain which vehicle went which direction. Table II shows the result of this line counting. Ground truth values were manually counted by looking at the footages.

TABLE II
Counting Result by Lines on BEV

	A to B	A to C	B to A	B to C	C to A	C to B	Total
Ground Truth	11	5	3	34	4	38	95
Counted	8	4	2	19	3	19	55
Percentage	72.7%	80.0%	66.7%	55.9%	75.0%	50%	57.9%



Fig. 15. Counting Traffic by Lines on BEV

3.3 Experiment Results

Table III indicates the result of the proposed method. For the direction of ‘B to C’ and ‘C to B’, the proposed method detects the 5 broken trajectories in total and replaces them with the well-tracked trajectories from perspective 2. By doing so, the percentage of these two items improved about 6 to 8 percent. Also, for the overall accuracy of counting, the proposed method improves the accuracy by 5.3%.

TABLE III
Counting Result after Applying the Proposed Method

	A to B	A to C	B to A	B to C	C to A	C to B	Total
Ground Truth	11	5	3	34	4	38	95
Proposed	8	4	2	21	3	22	60
Percentage	72.7%	80.0%	66.7%	61.8%	75.0%	57.9%	63.2%

3.4 Discussion

As shown in Tables I and II, the accuracy is only about 60% even after the proposed method is applied, even though directions B and C account for about 75% of the total traffic volume. There are more than 30 vehicles that the proposed method was not able to detect and replace with. One of the possible reasons why this happens is the ID transfer, which is one type of ID switch.

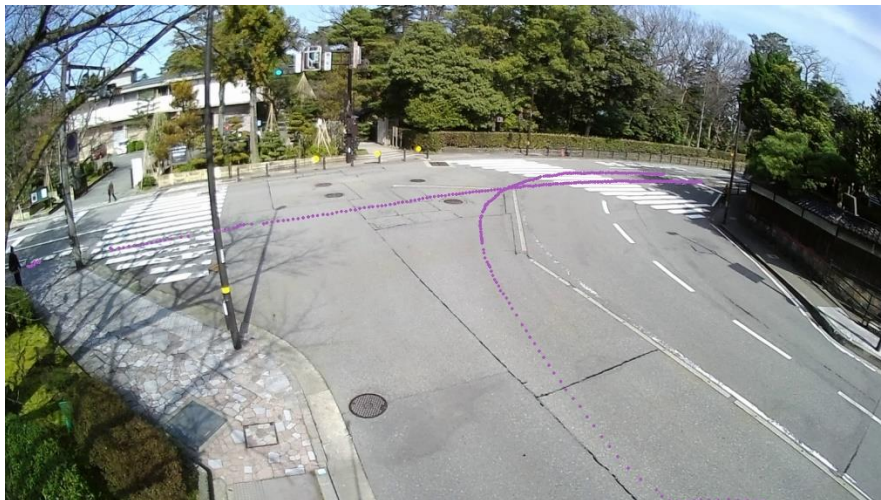


Fig. 16. An example of ID transfers

ID transfers are very likely to happen when the tracked objects come across within an image. Figure 17 shows an example of trajectories that an ID transfer happened in the middle of it. This results in ID duplications and generating much longer trajectories that pass through across the intersection more than once. Since the proposed method focuses on complementing the broken trajectories in the ROI, it cannot handle such ID transfers. If we apply the proposed method to the tracking results that contain less ID transfer and a lot of ID Re-Initialization, the improvement of counting accuracy will increase. Nevertheless, to count traffic more accurately even if the tracking results include a lot of ID transfers, extending the proposed method to deal with the ID transfer is important.

4. Conclusion

In this paper, I proposed a bird's-eye view transformation method that addresses situations in which a camera with a low position and wide-angle distortion is used. Additionally, I proposed a method to complementing vehicle trajectories on the transformed bird's-eye view to handle occlusion events. To evaluate the effectiveness of the proposed method, I evaluated it on real-world traffic data from two intersections in Japan. The proposed method resulted in a 5.3% improvement in the overall accuracy over automated counting using a single viewpoint.

In future work, one significant improvement of this proposed method is extending it be able to handle the ID transfers for counting more accurately even if the tracking algorithm used tends to generate ID transfers.

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