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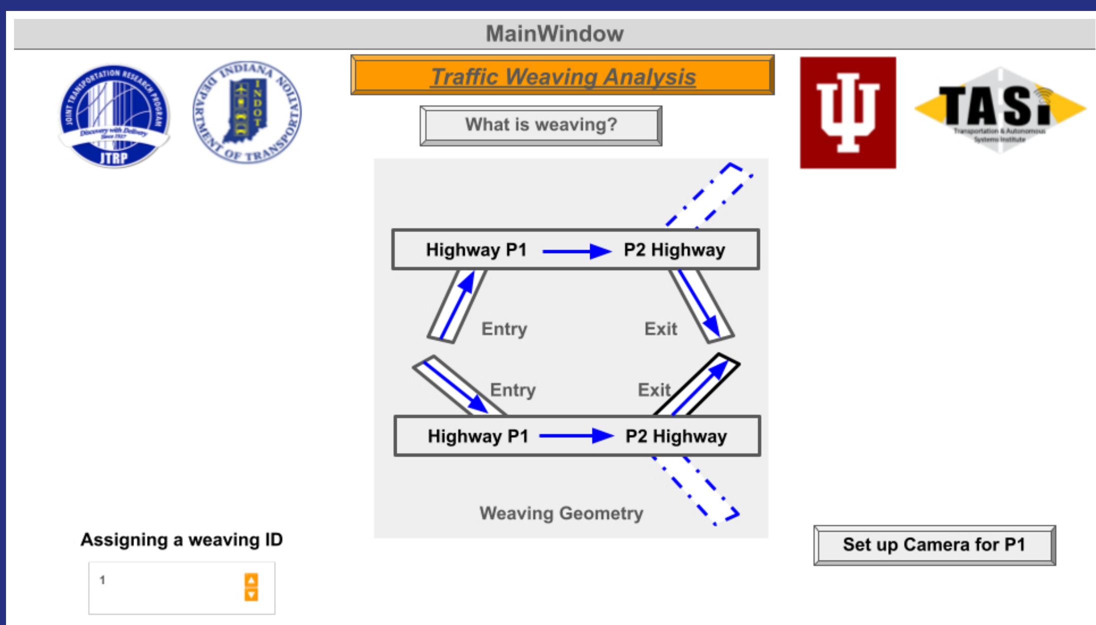
Origin-Destination Vehicle Counts in Weaving Area Utilizing Existing Field Data



Stanley Chien, Lauren Christopher, Yaobin Chen, Mei Qiu, Wei Lin

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AUTHORS

Stanley Chien, PhD
Professor of Electrical and Computer Engineering
School of Engineering and Technology
Purdue University in Indianapolis
(317) 274-2760
schien@iupui.edu
Corresponding Author

Lauren Christopher, PhD
Associate Professor of Electrical and Computer Engineering
School of Engineering and Technology
Purdue University in Indianapolis

Yaobin Chen, PhD
Director of TASI, Professor of Electrical and Computer Engineering, Chancellor's Professor
School of Engineering and Technology
Purdue University in Indianapolis

Mei Qiu
Wei Lin
Graduate Researchers
School of Engineering and Technology
Purdue University in Indianapolis

JOINT TRANSPORTATION RESEARCH PROGRAM

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NOTICE

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16. Abstract

Vehicle weaving describes the vehicle lane changes in areas between consecutive merge and diverge ramp junctions. During heavy traffic, vehicle weaving will slow down traffic, cause congestion, and increase the possibility of crashes. It is desirable to automatically capture the weaving information using camera videos in the weaving areas. The currently existing weaving area analysis is very tedious and labor-intensive. This report describes a novel system that uses the videos simultaneously captured at the entry and exit of the weaving area to find the number and percentage of vehicles from each lane on the entry to each lane on the exit. The system provides a convenient user interface, uses AI techniques to detect vehicles from camera videos, uses vehicle motion to identify the lanes, tracks and matches the vehicles at the entry and exit in the lane level, and presents the weaving analysis result in a user-friendly Sankey diagram. Compared to the other existing weaving analysis methods, this system can reduce the human work hours by at least 90%.

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EXECUTIVE SUMMARY

Introduction

Vehicle weaving describes the trajectories of vehicles that change lanes in areas between ramp merge and diverge junctions. During heavy traffic, vehicle weaving will slow down traffic, cause congestion, and increase the possibility of crashes. The Indiana Department of Transportation (INDOT) may need to modify weaving areas to reduce congestion and improve safety; however, the modifications must be determined by traffic analysis using origin-destination data on the percentage and pattern of vehicle weaving. INDOT has cameras installed in urban areas on the interstate system and in many weaving areas to capture this information.

Findings

The Transportation and Autonomous Systems Institute (TASI) of the Purdue School of Engineering and Technology at Indiana University-Purdue University Indianapolis (IUPUI) and the Traffic Engineering Division and Traffic Management Center of INDOT worked together to develop a system that uses the videos simultaneously captured at the entry and exit of the weaving area to find the number and percentage of vehicles from each lane on the entry to each lane on the exit. The developed system was implemented in INDOT. The system has the following features.

1. User-provided weaving area information.

The system has an interface for the user to provide the entry and exit locations, and the number of lanes and approximate lane centers of the weaving area on the entry and exit camera images.

2. Vehicle detection.

Since the camera sees the road at an angle and the vehicle center is the easiest and most accurate location for vehicle counting, the lane center that the camera sees shifts from the actual lane centers. Therefore, the vehicle trace is used to determine the lane locations. Automatic vehicle detection is an essential part of this project. The AI-based object detection method, YOLOv4, is used for vehicle detection in various lighting and traffic conditions. As a result, vehicle detection accuracy in an automatically selected region of interest can reach over 90%.

3. Road boundary detection.

Since objects off the road can occasionally be falsely detected as vehicles, the tracking information of detected moving vehicles is used to determine road boundaries. Therefore, only the vehicles detected on the road are considered for traffic condition checking. This knowledge of road location helps to eliminate vehicle detection errors.

4. Lane detection.

The lanes are statistically determined by tracing the vehicle motion at the reference lines on the road, since most vehicles remain in the same lane mostly in the region(s) of interest.

5. Vehicle count and classification.

The vehicles on each lane of the entry and exit are counted and time stamped. The vehicles are classified into two types—cars, and trucks.

6. AI-based vehicle match.

The features of all vehicles detected are extracted. The feature matching score of every pair of vehicles, one at the entry and one at the exit is generated. The vehicle pairs with a high match score are further examined through filters to reduce false positive matches.

7. User verification of matched vehicles.

A user-friendly interface program presents the pictures of each pair of matched vehicles to let the user verify if they are true or false.

8. Generation of the weaving analysis result.

The total number of detected vehicles is counted. The percentage of counted vehicles from each lane in the entry to each lane in the exit can be identified. By considering the truly matched vehicles as a sample of the total vehicles, we can estimate the number and percentage of vehicles from each lane in the entry to each lane in the exit.

9. Hardware specification.

A Linux PC with a relatively low-end GPU and CPU (e.g., a $1,500 PC) is sufficient to run the developed software tool in this work.

Implementation

The current methodology for origin-destination counts in the weaving area are manual analysis methods, which are very tedious and labor intensive. As a result, these counts are not undertaken frequently, leading to many assumptions. The main contribution of this study is to develop and implement an efficient and accurate method for traffic origin-destination counts in the weaving area, which reduces the person-hours by at least 90% compared to the manual counts.

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1. INTRODUCTION

Vehicle weaving is the action of lane changing of vehicles in weaving sections on highways. Weaving section is defined in the *Highway Capacity Manual* as, "A length of one-way roadway" serving as an elongated intersection of two one-way roads crossing each other at an acute angle in such a manner that the interference between cross traffic is minimized through substitution of weaving for direct crossing of vehicle pathways. One can interpret that weaving sections refer to areas of the highway where there is an entrance or exit ramp. Vehicles in areas of weaving sections are often forced to perform lane changes to merge into the highway from an entrance ramp or diverge from the highway to an exit ramp. During heavy traffic, weaving sections would contribute to slowing down the traffic, causing congestion, and having a higher possibility of crashes. Highway design needs to be modified in heavy weaving sections to improve safety and operations. Decisions on where those sections need to be modified are built upon analyzing the traffic weaving at the weaving areas.

Traditional ways of collecting traffic weaving data include probe data (the data collected by monitoring the position of vehicles over time and space), roadway sensors, or counting based on a video recording by a human. Probe data can provide meaningful information that can contribute to the traffic weaving analysis; however, they only provide road-based but not lane-based information. Roadway sensors can provide an accurate count of the vehicles moving through lanes but still cannot provide information on how vehicles change lanes in the weaving area. License plate identification and matching techniques can be used for lane-based weaving analysis. However, it needs a particular camera setup in order to be able to see vehicles' license plates clearly enough for vehicle identification on multiple lanes on the highway and ramps. The current method for weaving analysis is by human observation and counting from a video recording, which is very labor-intensive. During rush hours, it could be difficult for humans to count the vehicles and recognize the weaving patterns in a weaving area. This research focused on identifying, counting, and matching the vehicles based on video input from highway or drone cameras using AI techniques. This method can significantly reduce the need for human labor-intensive counting. Given a weaving area geometry (as shown in Figure 1.1), where the entry and exit can be on either side of the highway and no other entries or exits between P1 and P2, the goal is to find the following based on the videos recorded at P1 and P2.

1. The percentage of vehicles on the highway continuing to the highway.
2. The percentage of vehicles on the highway going to the exit.
3. The percentage of vehicles on entry going to exit.
4. The percentage of vehicles on entry going to highway.

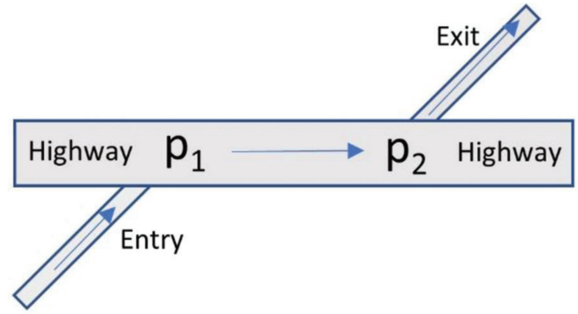

Figure 1.1 A weaving geometry example.

2. TRAFFIC WEAVING ANALYSIS TECHNIQUES

This section discusses the techniques related to traffic weaving analysis. To identify traffic weaving, we need to understand what traffic weaving is about and the techniques relevant to our research approaches.

According to the definition from the *TRB Highway Capacity Manual*, weaving is "defined as the crossing of two or more traffic streams traveling in the same direction along a significant length of highway, without the aid of traffic control devices (except for guide signs)." The analysis of traffic weaving is crucial for understanding the impact of lane changing on traffic flow and safety. Our primary focus is on the lane-changing behavior of vehicles at the entry and exit points of the highway. Understanding the factors that influence traffic weaving can provide valuable insights to improve traffic flow and the safety of the weaving areas.

2.1 Vehicle Detection

Vehicle detection is a problem in computer vision that involves identifying objects on a given image or a video stream. The ability to automatically detect vehicles has many practical applications. There have been numerous advances in this topic over the past years, and AI-based methods are the most effective in vehicle detection. YOLO is one of the successful object detection methods that can be applied to vehicle detection. YOLO has several versions. YOLOv4 has quite good vehicle detection accuracy. The later version has incremental improvement in accuracy or execution speed. YOLOv7 (Wang et al., 2022) is the most recent version of YOLO, developed by the same team members who developed YOLOv4.

2.2 Vehicle Tracking

In weaving analysis, the exact vehicle shown on the different video frames cannot be counted as multiple vehicles. Therefore, the detected vehicles need to be tracked across several frames. Multiple object tracking (MOT) is a complex problem that involves tracking multiple objects over time in a given video. MOT aims to associate the objects from one frame to the next. Some challenges that exist in MOT are occlusion of the objects, objects disappearing from the scene, and objects that change appearance due to factors such as angle change.

Two types of tracking algorithms are used today: detection-free tracking and detection-based tracking. In detection-free tracking, an initialization of the objects is required to track the objects in the video. So, it does not require an object detection model to tell where the objects are, and the number of objects that can be tracked will be fixed because new objects will not be recognized. This method does not work in this research. The detection-based tracking algorithms, also known as tracking-by-detection, require an object detection model to be trained first. The input of the detection-based tracking algorithm is based on the output of the object detection model. This output is like automatically setting up the initialization process. However, if the performance of the object detection is low, it will directly impact the tracking performance. Since this algorithm is much more flexible, it is more popular today.

There are many state-of-the-art detection-based tracking algorithms. Of the state-of-the-art tracking algorithms, DeepSORT is the most popular and frequently used in traffic surveillance applications. DeepSort uses deep learning to track objects in videos. It starts by detecting objects in each video frame using models like YOLO or Faster R-CNN. DeepSort then extracts deep features for each detected object to track them accurately. It links objects across frames based on features and spatial information, uses Kalman filtering for prediction, assigns unique IDs to tracks, and handles occlusions. The output is a set of object tracks with IDs, showing their paths in the video.

2.3 Vehicle Feature Extraction

Since a single camera usually cannot cover both the entry ramp and the next exit ramp in a weaving area, and the camera that captured the video at the entry cannot overlap that at the exit, continuous vehicle tracking from the entry to the exit is not feasible. It is essential to match vehicles detected and tracked on the entry and that on the exit. Vehicle matching is also called vehicle re-identification in the AI field. Vehicle re-identification requires two parts: the first is the vehicle feature extraction, and the second is the vehicle feature matching. Features of vehicles with vast amounts of makes, models, colors, and viewing directions are complex to describe. AI method, DeepSORT, can be used to generate feature vectors of large dimensions. The output of the feature is a fixed-length array of numbers, and those numbers may not have an intuitive connection to the physical appearance of the vehicle features, but they do effectively represent the physical appearance of the vehicles.

Cosine similarity (Prabhakaran, 2022) can be applied to find the similarity of the feature vectors. Cosine similarity is a widely used measure in data analysis and machine learning that calculates the cosine of the angle between two non-zero vectors. By applying the calculation, we can evaluate how closely related the two input feature vectors are. The output range of cosine similarity is from -1 to 1. An output value closer to 1 indicates that the two feature vectors are close to each other, while a value closer to -1 indicates that the two feature vectors are not similar.

3. METHODOLOGY

This research aims to use the videos captured at the entry and exit of a waving area to determine the weaving pattern. To support the weaving analysis accuracy, a video capturing guideline (see Appendix A) has been developed to help the user set up the camera viewing angle (and distance if possible) at their interested weaving area to get the best quality video possible.

A framework consisting of several steps was developed for weaving analysis (Figure 3.1). The first step is to collect location and video information about the weaving area from the user. A GUI was developed to guide the user to provide this information effortlessly. Then, the recorded traffic camera videos are loaded. YOLO vehicle detection and DeepSORT tracking algorithms are used to detect and track all the vehicles that go through the entry and exit videos. The lanes from the perspective of the camera viewing angle are learned, so the detected and tracked vehicles are assigned to specific lanes on highways and ramps. An AI method extracts features for each detected/tracked vehicle. The features of detected vehicles at the entry and exit are matched. To ensure the accuracy of the result, the user is asked to verify an AI-generated

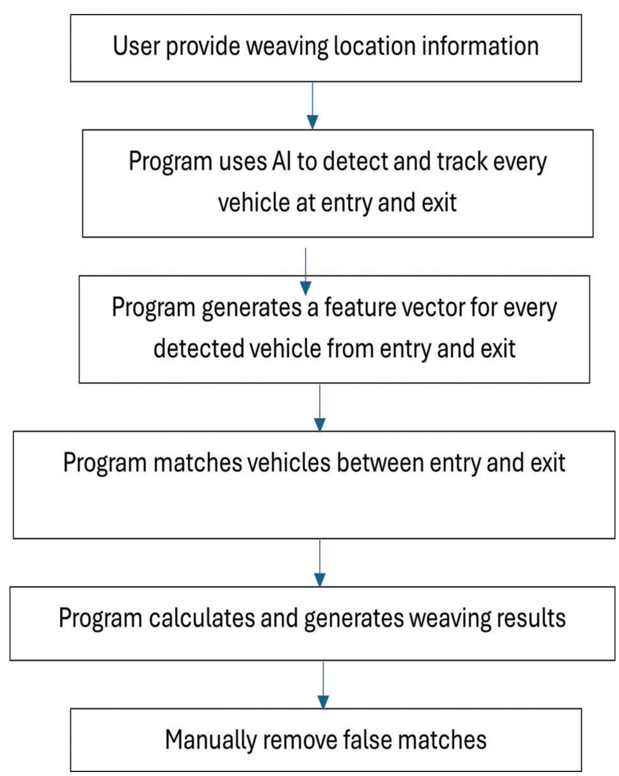

Figure 3.1 The framework for weaving analysis.

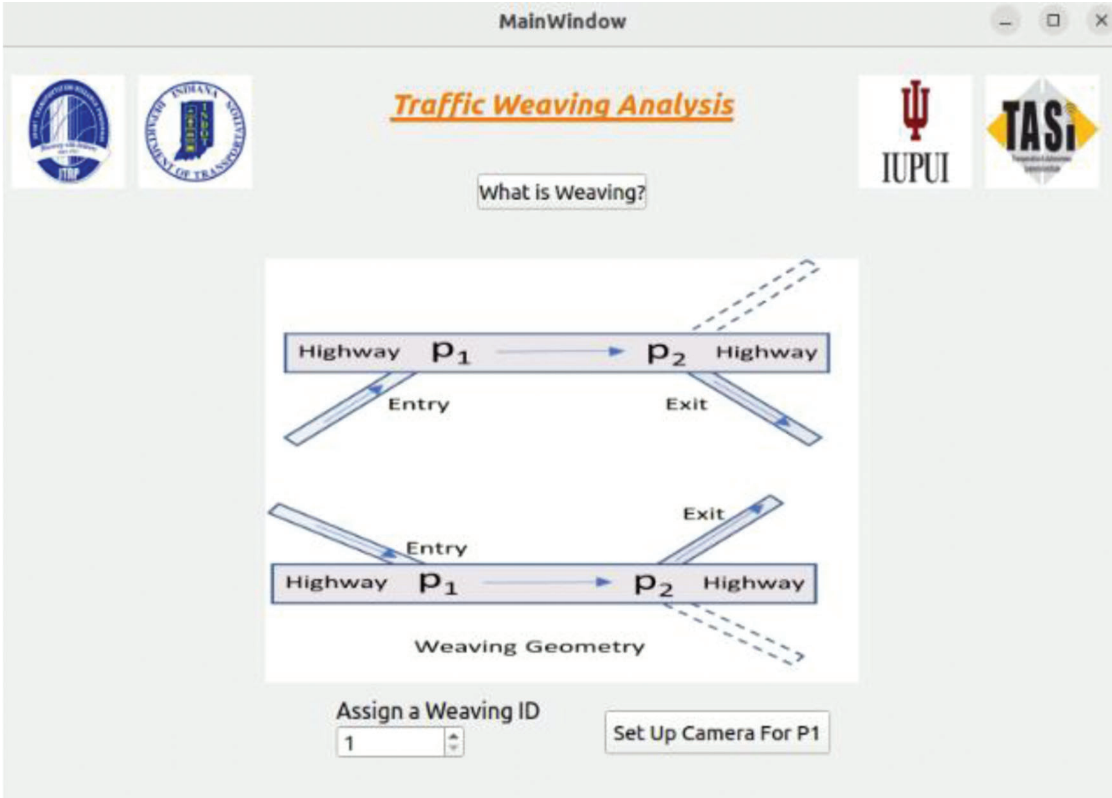

Figure 3.2 The first page of the weaving area information gathering GUI.

vehicle match to keep the actual match and eliminate the false matches. The number and percentage of vehicles from each lane at the entry to each lane at the exit can be calculated and derived using the information of truly matched vehicle pairs.

3.1 User-Provided Weaving Location Information

INDOT has installed hundreds of cameras around Indiana highways. The users need to specify the weaving area they are interested in, i.e., the entry and exit locations, the path of the recorded video at these locations, and where the vehicles should be counted on the video. A graphic user interface (GUI) for weaving area information gathering is designed to guide the users to provide information quickly. The GUI first shows a title page (see Figure 3.2). At the bottom of the page is a button *Set Up Camera for P1* to navigate to the next page and an input field for assigning a weaving ID. The weaving ID is a case identifier for the user's future reference. Users can assign any numerical ID they wish. It will not affect the program execution.

On the following GUI page (Figure 3.3), users are prompted to input the file path for the video recording associated with the weaving case. To facilitate this, users can click the *browse* button, which opens a file navigator, enabling them to select the desired video file easily. Once the selection is made, the file path will be displayed below the *browse* button for reference and confirmation. Notably, for user convenience, an image representing the entry location will be displayed prominently on the page when selecting the entry location video, serving as a helpful visual cue to ensure users understand the context of their selection. Likewise, when users are asked to choose the exit location video, the page will display an image corresponding to the exit location.

After the user inputs the recorded video file path, the user is asked to specify the Region of Interest (ROI) on the video for vehicle counting and other information that the user can easily provide, such as the reference baselines of the highway and the ramp, lane centers on the road, number of lanes in each of the baselines, and the direction of traffic (Figure 3.4). The baseline is a reference line in an ROI. This line should be located where the camera can see vehicle details. Lane centers are where the human-perceived lane centers are located at the selected baseline. The number of lanes is on the baseline in the ROI. The direction of the traffic is if the traffic is moving down or up in general. A similar user interface repeats the entry and exit locations of the weaving area. With the user-provided information, the program can analyze the weaving patterns.

3.2 Vehicle Detection and Tracking at Entry and Exit Using AI

Since the intended weaving analysis needs to determine how many vehicles on each lane of the entry location are going to each lane at the exit location, the

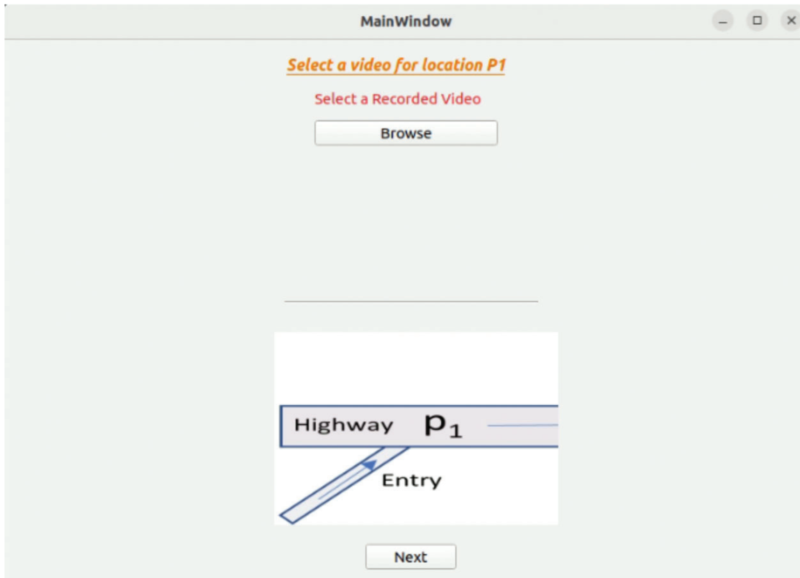

Figure 3.3 Page 2 of the GUI asks the user to provide the path of the recorded video.

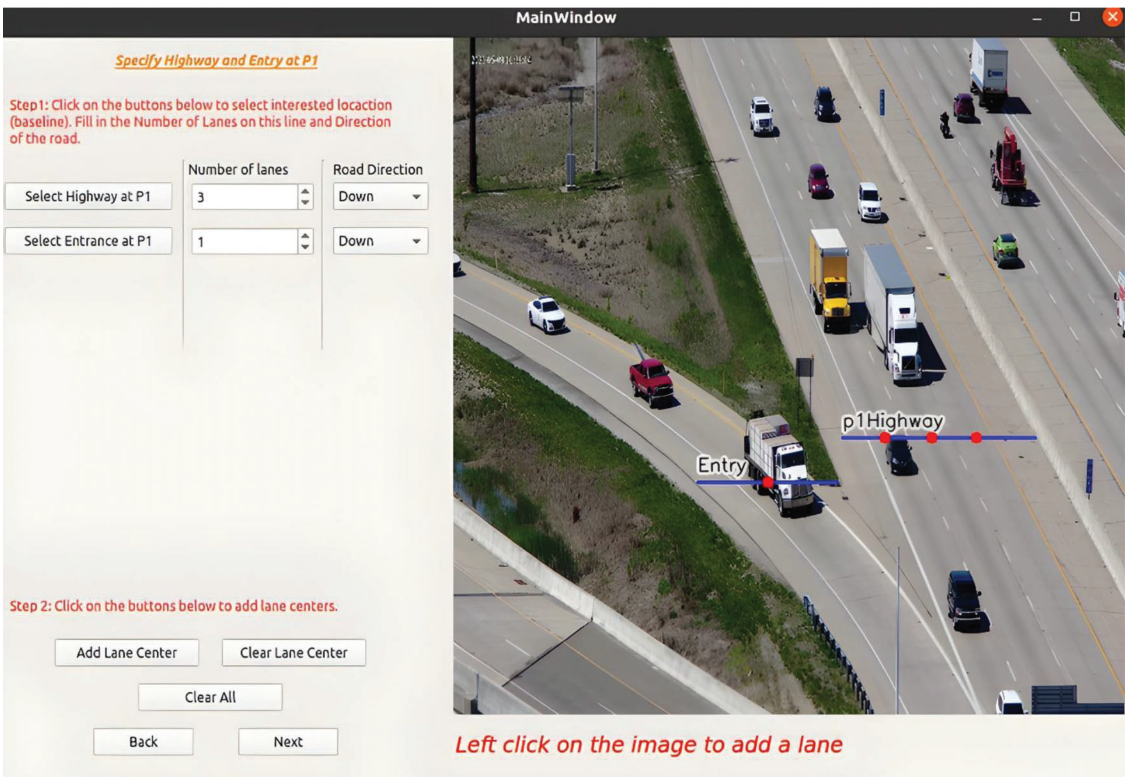

Figure 3.4 The user specifies (a) the baseline location as shown in the blue line, (b) the lane centers that are on the baselines as shown in the red dots, and (c) the number of lanes and the direction of the traffic flow in the textbox and the dropdown box.

lane location on the video is essential to assign detected vehicles to lanes. Although the user has provided the rough location of each lane center, they are from the user's bird-eye view perspective. Since the camera may see the road from an angle different from the bird-eye view, the lane center seen by the camera may be close but different from the user-provided lane centers. Therefore, the lane learning method (Qiu et al., 2021) is applied to learn the lane center locations from the camera viewing perspective. The user-defined lane centers are references to determine the accuracy of the learned lane centers.

The lane centers at different road points within the ROI are detected, and the adjacent lane centers

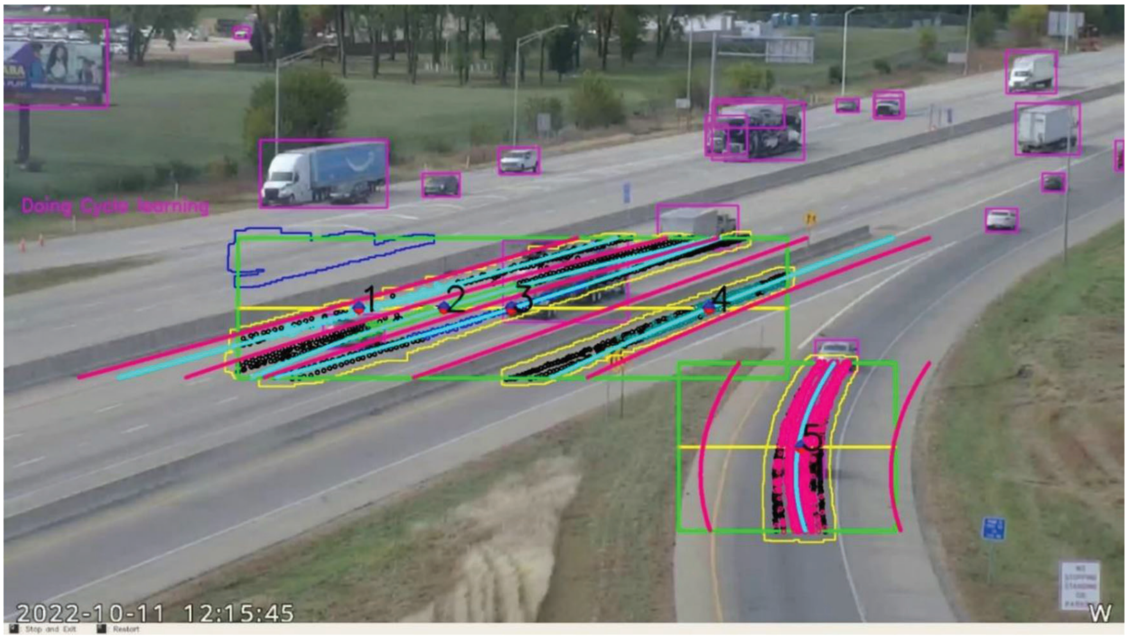

Figure 3.5 Result of the learning process.

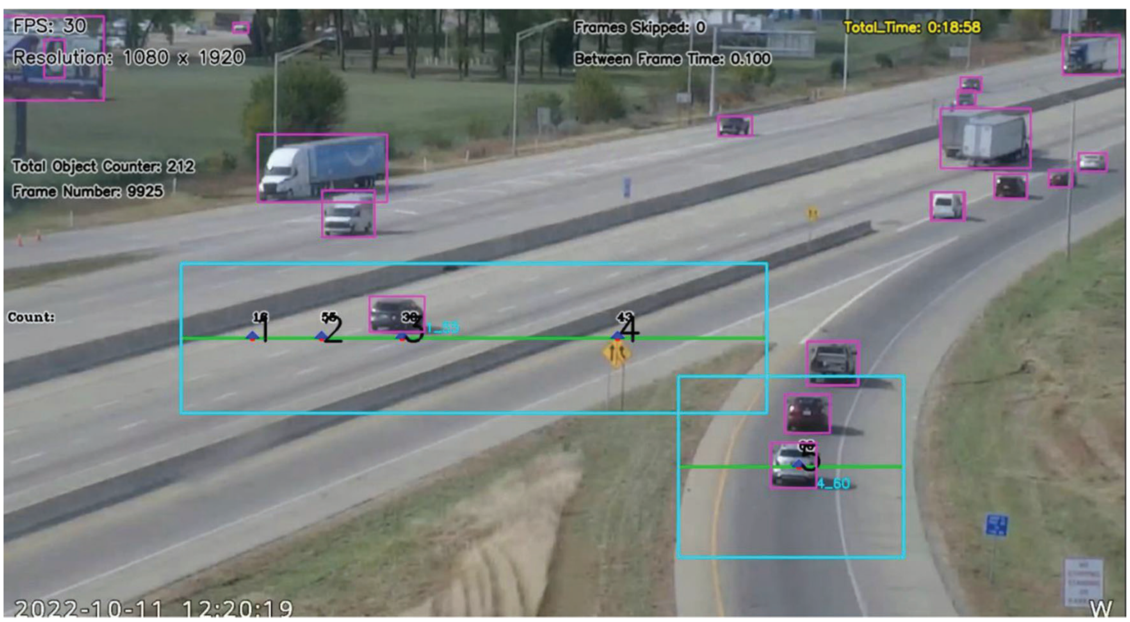

Figure 3.6 Vehicles counted for each lane.

are grouped to determine the lanes. The lane center (pink line) is generated by curve fitting for each group of adjacent lane centers. The lane boundaries (yellow contour) are derived from lane centers (see Figure 3.5).

After the detection of the lanes, the center location of all detected and tracked vehicles can be associated with lanes in the ROI, and the vehicles going through each lane can be counted (see Figure 3.6).

We used YOLOv4 to detect vehicles. Although newer iterations of YOLO were available during the course of our research, we did not adopt the newer iterations for several reasons. First, our YOLOv4 model had undergone extensive training yielding a level of accuracy that satisfied the requirements of our study. Training newer versions of YOLO would cost time and resources, with only potential marginal gains in accuracy. Second, while the newer YOLO versions enhanced real-time performance, our research primarily focused on post-processing analysis rather than real-time. Thus, it is not a priority for us to update the analysis to newer versions of YOLO.

DeepSORT was used as our vehicle tracking algorithm as it is the best for the feature extraction we tested. The feature extractor directly impacts how well the vehicles can be matched. Thus, with better training, or a better model of the feature extractor we might be able to obtain a better performing system. However, as we did not have the time to perform tests on many other feature extractors, this could be studied further.

3.3 Vehicle Feature Extraction and Matching

3.3.1 Feature Extraction

The detected vehicles are first cropped from the video frames to focus on getting the features of detected vehicles and reducing the noise generated by surrounding objects. Then, the feature extractor produces a feature vector for each cropped vehicle image. Luo et al. (2019) and DeepSORT (Wojke et al., 2017) can generate a feature vector based on the cropped vehicle image. By comparing the performance of both algorithms, it was found that the feature extractor by Luo et al. (2019) has a better quality. We also used the VeRi776 (Liu et al., 2016) dataset combined with our own dataset to further train this re-identification model by applying the transfer learning method to reach better accuracy.

3.3.2 Vehicle Matching

We need to match the entry vehicles with the exit vehicles as those vehicles travel from the entry to the exit. The total number of possible pairs of vehicles that we need to compare will be given by $V_{entry} \cdot V_{exit}$. However, it should be noted that the maximum number of correct match pairs may be lower or equal to the minimum of V_{entry} and V_{exit} because each entry vehicle should be matched with at most one exit vehicle.

Vehicle matching between the entry and exit is measured using cosine similarity. The cosine similarity score should be 1 when the vehicles are identical and closer to -1 if the vehicles are entirely different. We experimentally set a threshold value for cosine similarity to eliminate most false matches while keeping the accurate matches. This is important because it may be challenging to obtain the actual matches buried in them with too many false matches. However, the program-generated matches still have a significant number of false matches (over 90% are false matches).

In this vehicle matching process, the features of every vehicle detected from entry are compared with those from exit. The cosine similarity checking program generated a result showing a many-to-many vehicle relationship. This is a problem because, realistically, an entry vehicle should only be matched with at most one exit vehicle, which is a one-to-one relationship. This can be demonstrated by Figure 3.7. The row represents the vehicles detected in all frames of the entry video. The column represents the vehicles detected in all frames of the exit video. Each white dot shows a program-generated vehicle match which passes the cosine similarity threshold value. In fact, only the white dots on the faint upper-left to bottom-right line has a high probability of being true vehicle matches and all other white dots are false matches.

3.3.3 Filtering Out False Matches

A set of filters was adopted to filter out the false matches.

Filter 1: Remove matches where the frame time at entry is later than the time at the exit.

In a weaving area, vehicles are flowing in one direction only, thus it is not possible for a vehicle to be observed at exit before it has been observed at entry. Assuming that the videos at entry and exit were being recorded simultaneously, the vehicles at entry with a later timestamp and those at the exit with an earlier time stamp must be a false match. A significant number of false matches can be removed using this criterion. Since cameras used at the entry and exit may have different frame rates, the frame number needs to be upscaled if it has a lower FPS than the other video. The frame ID of the low FPS video can be scaled up using the following equation.

$$Frame\ Number_{upscaled} =$$

$$round\left(Frame\ Number_{original} * \frac{FPS_{higher}}{FPS_{lower}}\right)$$

Filter 2: Remove matches with vehicles of different types.

YOLO vehicle detection can distinguish the vehicles by type of cars and trucks. The type information is associated with every detected vehicle. The type of vehicle at the entry and exit are checked. If they are different, the match is considered false. It is worthwhile to note that this filter does not eliminate a significant number of false vehicle pairs.

Filter 3: Time filter.

The average speed of vehicles in a weaving area does not change in a short period most times. If the travel time from the entry to the exit can be found, the vehicles that matched not around this travel time are considered false matches. The main task of this filter is to find a range of the travel time for vehicles. To identify the traffic time, we assumed that there will be more vehicle matches around the average travel time from the entry to exit, if the extracted features can help vehicle match. Therefore, the following equation is used to assign a "score" to different traveling time, *t,* in all matched vehicle pairs, where k is the number of frames that results in travel time t.

$$Score\ t_t = \frac{\sum_{v=0}^{n} cosine\ similarity\ score}{k}$$

The plot of score versus traveling time for actual weaving data is shown in Figure 3.8. The resulting graph has three different lines. The graph's horizontal axis represents the travel time, and the vertical axis represents the average sum of the cosine similarity score

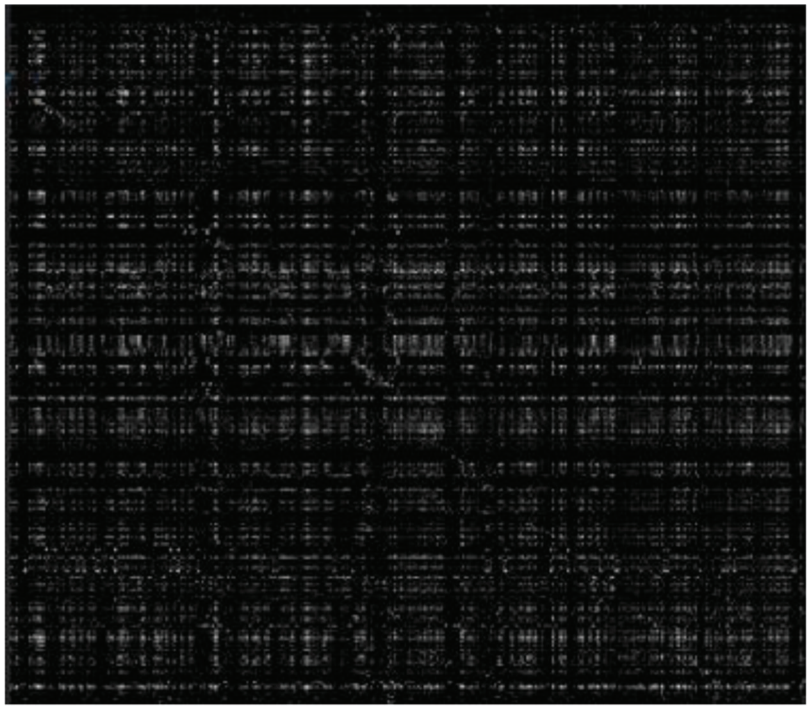

Figure 3.7 Example of program-generated vehicle matching results.

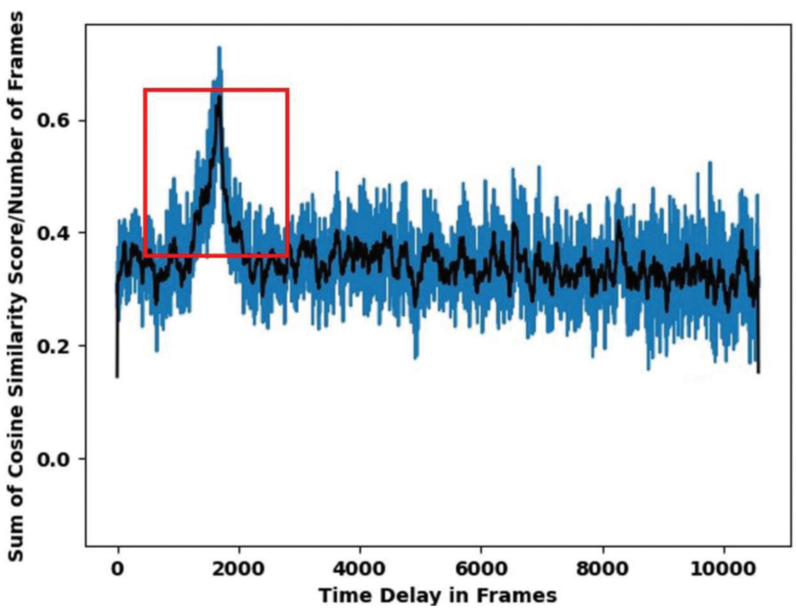

Figure 3.8 The plot of score versus traveling time for actual weaving data.

over the k frame window. The blue color represents the collection of original vehicle match points, and the black line represents the smoothed data values after applying an average filter of window size five. The traveling time with the highest score, as shown in the red box, is considered the trustable traveling time from the entry to the exit.

Since there are variations in the travel time due to different vehicle speeds, we divided the data in 10 minutes segments. In each 10 minutes segment, we assume that the vehicle speed is relatively consistent. For the small vehicle speed variations, we want to expand the acceptable vehicle travel time from a peak value into a range around the peak value. So, we expand the frame number from the peak frame number to the left and right until the value is always lower than the average cosine similarity score. Based on this range, we will remove all the vehicles outside this travel time. Please note that this is the travel time for most vehicles. It is possible to filter out some actual vehicle matches.

Filter 4: Remove inconsistent match based on the percentage of frames they were matched in all frames they were detected.

During the vehicle detection and tracking, each vehicle is detected and tracked over many image frames as it passes through the ROI. Thus, we have generated feature vectors for each vehicle at every frame as the vehicles pass through the ROI. Some vehicle matches are consistent throughout most frames where they were identified, but some vehicle matches only exist in a small portion of the frames where they were identified. The former is more likely to be an actual match. The latter is less likely to be an actual match. Therefore, this phenomenon removes less likely true (or more likely false) vehicle matches.

Filter 5: Remove duplicate matches.

In matching vehicles at entry and exit, each entry vehicle should be matched with one exit vehicle and vice versa at most once. However, even after applying the various filters discussed before, there is still a possibility that a vehicle can be matched with multiple vehicles. If a vehicle appears in multiple matches, the match with the highest score will be kept, and all others are considered false matches.

Summary of the Filters

Figure 3.9 shows the ground truth vehicle matches and the program generated before and after filtered vehicle matches.

Filters 1 and 3 can significantly reduce the number of vehicle pairs; a high percentage of the pairs removed are false positive pairs. Specifically, all the vehicles removed in filter 1 should be false positive pairs since vehicles in a weaving area are flowing in one direction only. Filter 3 should remove most of the vehicles outside of the travel time for most of the vehicles, which could remove some of the actual matches but should be a small fraction compared to the false matches removed in this filter. Those two filters will significantly improve the precision of the matches and only slightly reduce the overall positive matches. Filters 2, 4, and 5 do not reduce as many vehicle pairs compared to the other filters. However, those filters are still significant. They could occasionally remove the true positives but much less than the number of false positives removed. It means that they can still improve the overall precision rate.

3.4 Improvement of the Vehicle Matching Accuracy

Even after filtering, the result described in Section 2.3 still has significant matching errors (It will be shown in Section 4.). We do not have a better way of using a program to filter out these errors now. However, these errors can be relatively easily identified by human beings. Assuming 1,000 vehicles are observed at entry and exit in 2 minutes, the user may need to compare $1{,}000 \times 1{,}000$ pairs of vehicles to find the car matches on 1,200 images (assume ten frames per second) without using our proposed method. It will take one person several days of intensive work to find all the matches. Assuming one can find the vehicle match for 50% of vehicles using our method, we only need to determine which of the 500 vehicle pairs are true match and false match, which takes about 1 hour to complete. We created a simple GUI to bring the matched vehicle pairs one by one and guide the user through the correctness checking of these matched vehicle pairs easily (see the user interface in Figure 3.10). After this step, a portion of all detected vehicles are matched, and all matched vehicles are actual matches with the user verification.

3.5 Tallying of the Results

After finding the accurately matched vehicle pairs between the entry and exit colocations, the number and percentage of vehicles from each lane at the entry and each lane at the exit can be tallied. Since only a percentage of the vehicles can be matched with high confidence, the result can be considered accurate samples, which can be converted back to the total vehicle population in the weaving area.

3.6 Presentation of the Results

The Sankey diagram is a perfect method to describe the weaving analysis results (see Figure 3.11). The colored bars on the left represent the lanes at the entry; the colored bars on the right represent the lanes at the exit. The widths of curves connecting the lanes on the left to the lanes on the right show the number and percentage of vehicles. Figures 3.11, 3.12, and 3.13 are from the same weaving case results, showing all vehicles, cars only, and trucks only, respectively. The detailed information is shown in the white text on the

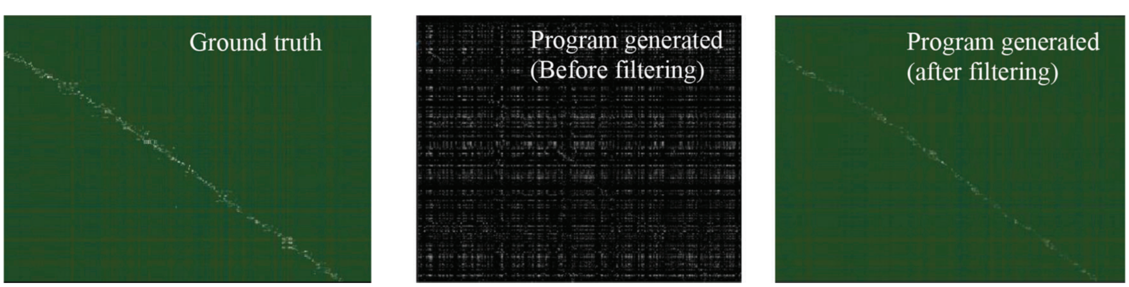

Figure 3.9 The comparison of ground truth, the program generated before and after filtering vehicle matches.

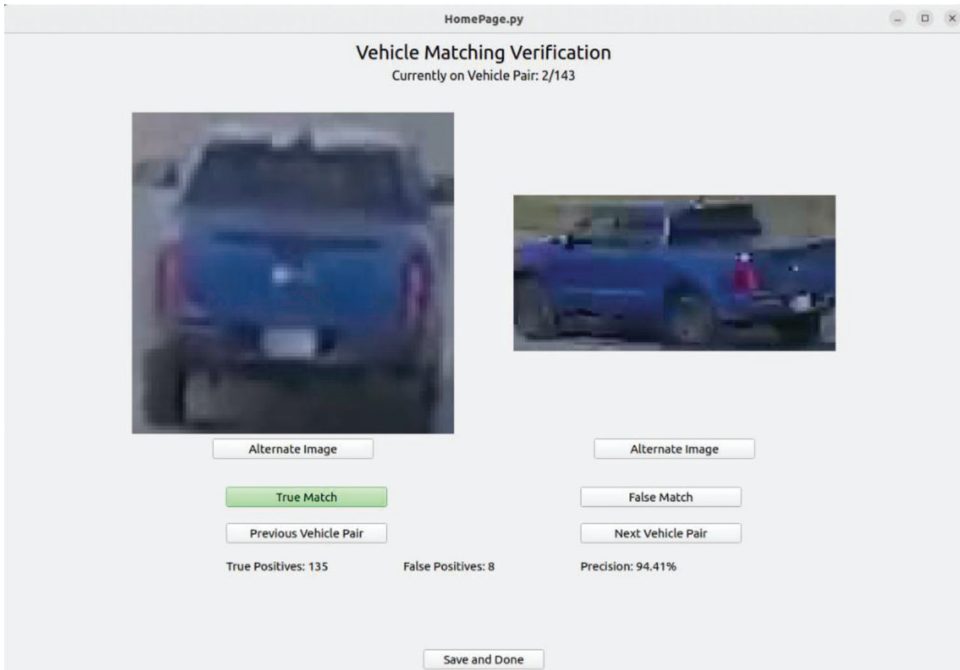

Figure 3.10 The user interface of vehicle matching verification.

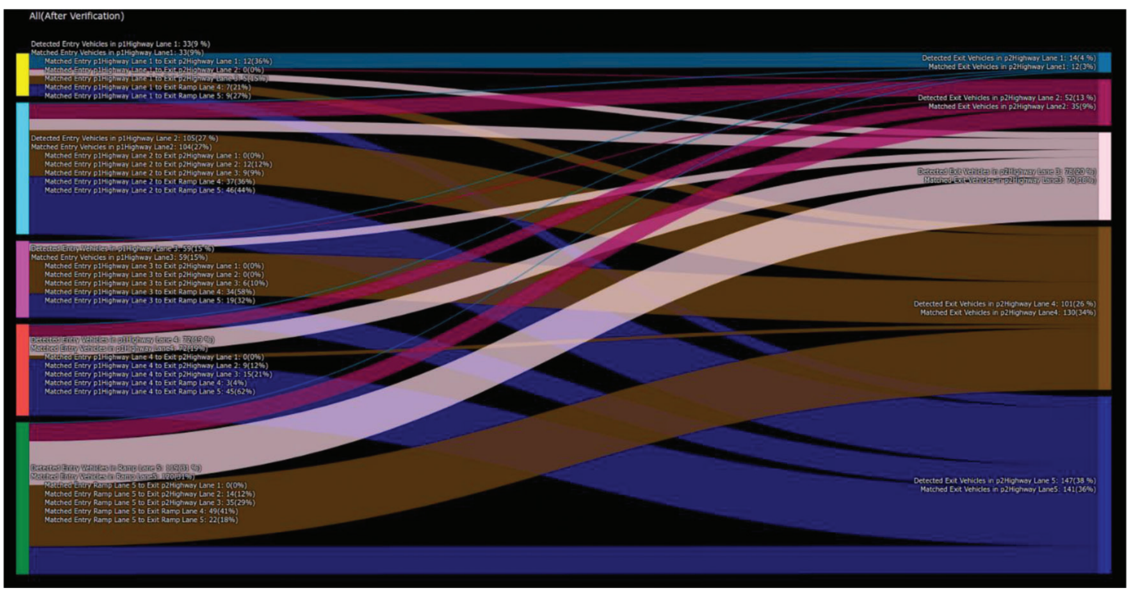

Figure 3.11 Sankey diagram for all vehicles after manual vehicle match verification.

diagram. Those numbers indicate the actual number of vehicles. We provided two different numbers: detected number of vehicles and matched number of vehicles. The detected number of vehicles presents the total count of the vehicles in the input video by the program, and the matched number of vehicles is the number of vehicles in the video sample that the proposed method found to match. The number of matched vehicles is a small sample of detected vehicles. The matched vehicles also have lane-specific information. Using this sample, we can provide expected results with certain confidence and better understand the actual number of vehicles driven from the entry to the exit rather than a small sample size.

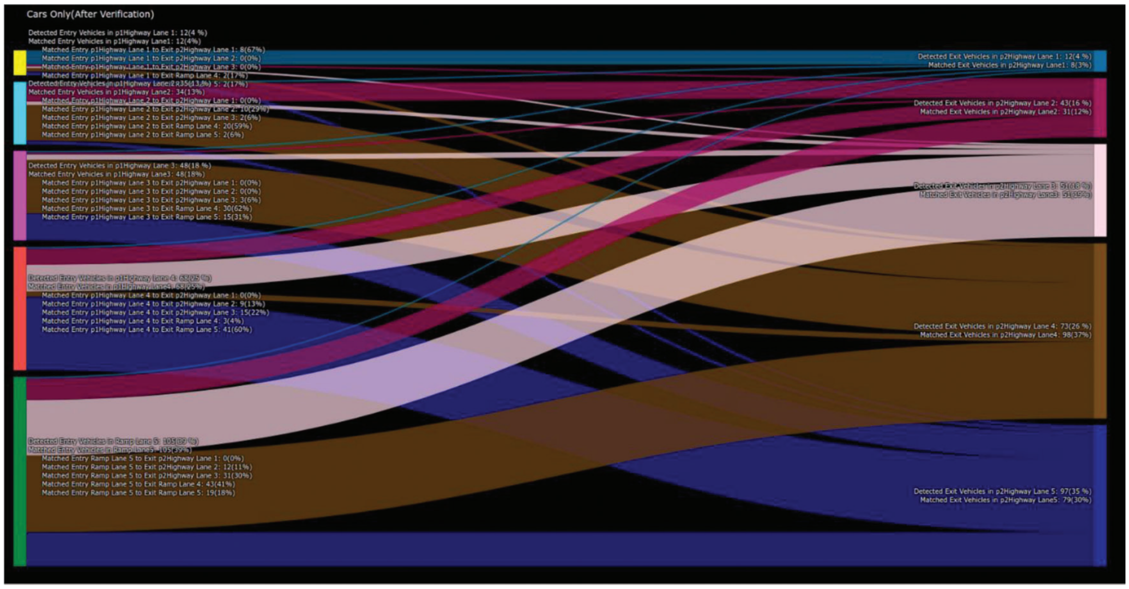

Figure 3.12 Sankey diagram for cars after manual vehicle match verification.

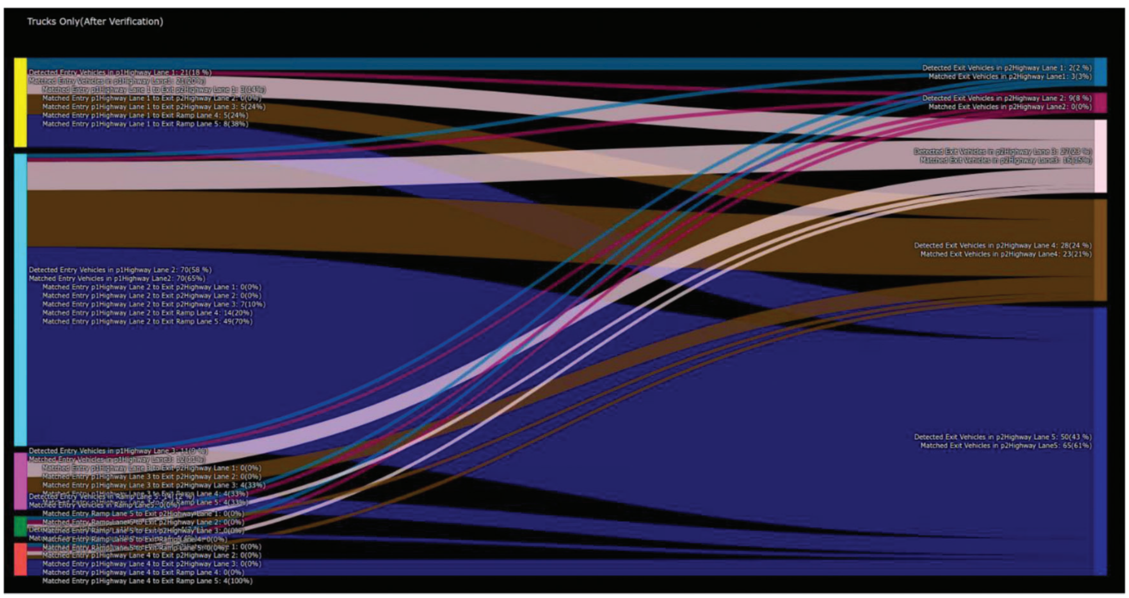

Figure 3.13 Sankey diagram for trucks after manual vehicle match verification.

4. EXPERIMENT RESULTS

This section presents the proposed weaving analysis results on a set of scenarios.

4.1 Experiment Setting

The program execution was conducted using a computer running Ubuntu 20.04 LTS. The hardware specifications of the computer are as follows.

- Hardware Model: Dell Inc. Precision 5820 Tower.
- Memory: 32 GB.
- Processor: Intel Xeon® W-2223 CPU @ 3.60 GHz × 8.
- Graphics card: NVIDIA Corporation TU1040GL Quadro RTX 4000.

4.2 Data Collection

The data collection process starts by identifying the weaving areas on Indiana highways. INDOT supported this process. Twelve weaving areas were identified for the experiment. Figure 4.1 to Figure 4.6 show the images of the entry and exit of six weaving areas.

In addition to the videos captured by highway cameras, we also used drones to record the desirable viewing angles. Such cases are shown in Figure 4.7 and Figure 4.8.

4.3 Ground Truth Data Generation

It is necessary to obtain the ground truth for the data that we have collected to evaluate the accuracy of the results that we generate from processing the recorded videos. This would involve reviewing every frame of the video and documenting the frame number and vehicle ID of each vehicle as it first appears, as well as the corresponding exit frame number and vehicle ID. Table 4.1 provides the format of the ground truth data we collected. The first column (entry vehicle ID) is the ID of the detected vehicle at the entry. The number before the underscore is the lane ID when the vehicle is detected, and the number after the underscore is the vehicle ID on that lane. The second column (entry vehicle number) is the frame number when the vehicle first appears.

Similarly, the third and fourth columns list the exit vehicle ID and exit frame number, respectively. Each row records a pair of matched vehicles at the entry and exit. This ground data was used to compare the results obtained from our proposed method.

In addition to the frame number when the vehicle's match appears, the table also provides the number of frames it takes to travel from the entry to the exit point. In the case shown in Table 4.1, the data suggests that it takes approximately 3,000 frames (100 seconds at 30 frames per second) to travel from the entry to exit. This timing information will be used later when we check the correctness of filter 3.

4.4 Quality of the Weaving Analysis Results

4.4.1 Analysis of Lanes Learned

This section describes the effectiveness of the lane learning module. All lanes must be appropriately learned to assign the detected vehicles to the proper

Figure 4.1 Weaving Area 1. Entry on the left, exit on the right.

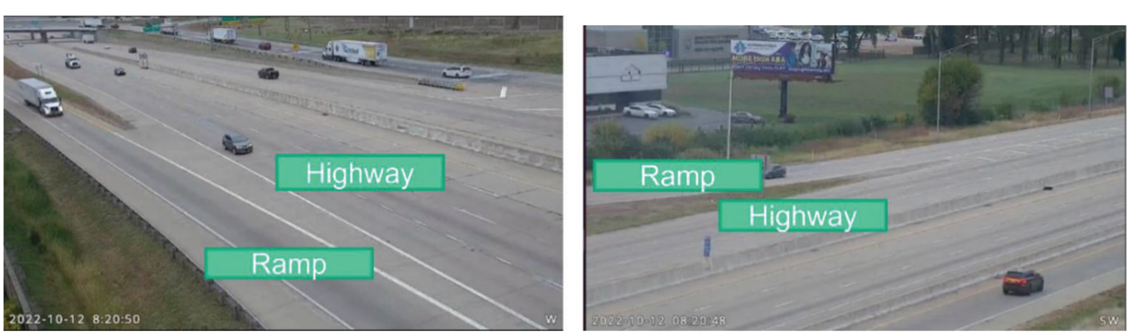

Figure 4.2 Weaving Area 2. Entry on the left, exit on the right.

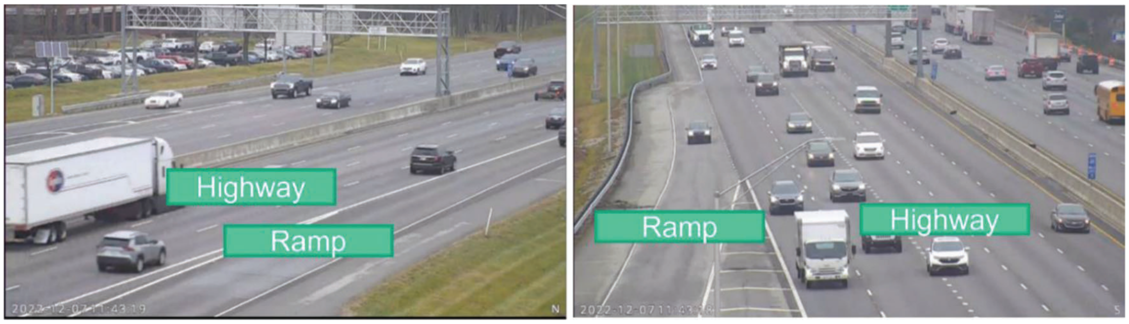

Figure 4.3 Weaving Area 6. Entry on the left, exit on the right.

Figure 4.4 Weaving Area 8. Entry on the left, exit on the right.

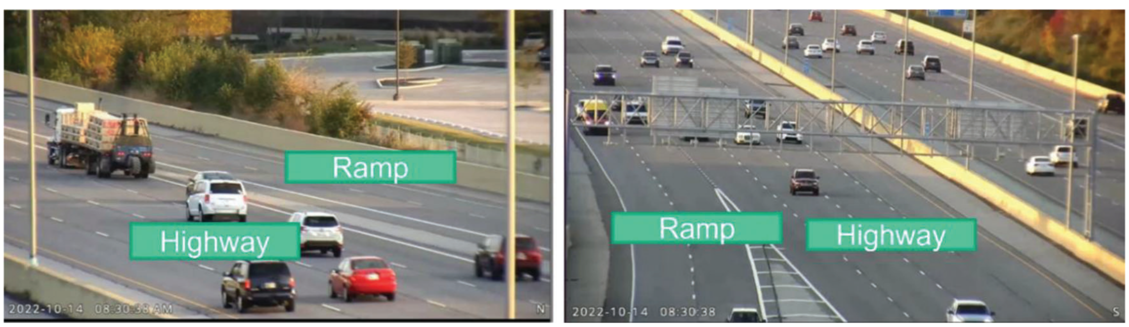

Figure 4.5 Weaving Area 9. Entry on the left, exit on the right.

Figure 4.6 Weaving Area 10. Entry on the left, exit on the right.

lanes. Figures 4.9 shows an example of the lane learning output results, and Table 4.2 gives detailed results of all the weaving cases. The data in the table indicates that the learning output of the framework is generally favorable across various scenarios that we tested, with the system successfully learning all the lanes on the road in most cases.

There are specific cases where the system did not capture all the lanes on the road. This is likely due to one of three reasons: either no vehicles were passing

Figure 4.7 Weaving Area 11. Captured by a drone camera (entry on the left) and a highway camera (exit on the right).

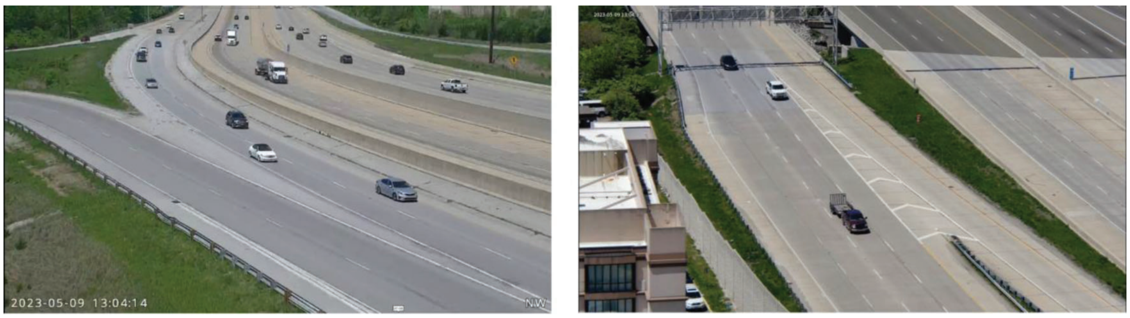

Figure 4.8 Weaving Area 12. Captured by a highway camera (entry on the left) and a drone camera (exit on the right).

TABLE 4.1
Example of ground truth data

Entry Vehicle ID	Entry Frame Number	Exit Vehicle ID	Exit Frame Number
1_2	4	4_39	3099
0_1	4	3_43	3095
2_1	4	1_20	3078
2_2	4	1_17	3067
2_3	4	2_33	3084
4_1	4	5_7	2870
2_3	31	4_38	3095
1_4	37	1_22	3266
2_4	60	0_48	3318
0_3	93	4_40	3198
2_5	154	2_38	3492
3_2	202	0_4	3360
0_5	256	2_36	3323
1_7	335	3_50	3464

through the lanes during the lane learning period (unless this lane is closed, this may not be the proper time to study the weaving behavior), or the camera viewing angle makes it challenging for the system to capture the lane (which may justify using drone to collect the data), or the sunlight angle causes poor video data (collecting data at a later time or using drone to collect the data in a different viewing angle).

4.4.2 Analysis of Vehicle Counting

Lane-based vehicle detection and counting at both entry and exit of a weaving area is an essential step in weaving analysis after lane learning. We use the recorded videos of 12 weaving areas as input to our system. Table 4.2 describes the camera location and setting for these weaving areas. The videos of each scenario are processed until the system has successfully counted 100 vehicles. We also manually count the vehicles by watching the same video. This manual count will be treated as the ground truth count and used to compare with the vehicle count by our proposed method. This comparison provides the accuracy of the system counting. Table 4.3 presents the experiment's outcomes, showing the counting accuracy of various cases, most of which exceed or equal to 95%.

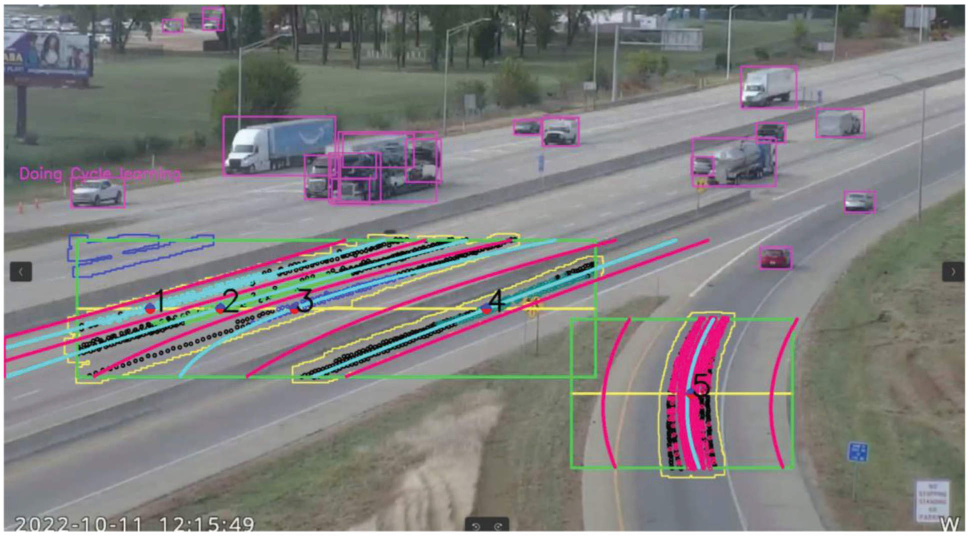

Figure 4.9 Example of the lane learning output.

TABLE 4.2
Lane learning results for all available weaving cases

Weaving Scenarios	Number of Lanes (ground truth)	Number of Lanes Learned	Accuracy (%)
Weaving 1 Entry Morning	5	5	100
Weaving 1 Exit Morning	5	5	100
Weaving 1 Entry Noon	5	5	100
Weaving 1 Exit Noon	5	5	100
Weaving 1 Entry Afternoon	5	5	100
Weaving 1 Exit Afternoon	5	5	100
Weaving 2 Entry Morning	5	4	80
Weaving 2 Exit Morning	5	3	60
Weaving 2 Entry Noon	5	5	100
Weaving 2 Exit Noon	5	5	100
Weaving 2 Entry Afternoon	5	5	100
Weaving 2 Exit Afternoon	5	5	100
Weaving 6 Entry Afternoon	5	5	20
Weaving 6 Exit Noon	6	6	100
Weaving 8 Entry Morning	3	3	100
Weaving 8 Exit Morning	4	4	60
Weaving 8 Entry Noon	3	3	100
Weaving 8 Exit Noon	4	4	100
Weaving 8 Entry Afternoon	3	3	100
Weaving 8 Exit Afternoon	4	4	100
Weaving 9 Entry Morning	6	6	100
Weaving 9 Exit Morning	5	5	100
Weaving 9 Entry Noon	6	6	100
Weaving 9 Exit Noon	5	5	100
Weaving 9 Entry Afternoon	6	6	100
Weaving 9 Exit Afternoon	5	5	100
Weaving 10 Entry Morning	6	6	100
Weaving 10 Exit Morning	6	6	60
Weaving 10 Entry Noon	6	4	67
Weaving 10 Exit Noon	6	6	100
Weaving 10 Entry Afternoon	6	5	83
Weaving 10 Exit Afternoon	6	6	100
Weaving 11 Entry (Drone Camera)	4	4	100
Weaving 11 Exit	4	4	100
Weaving 12 Entry (Drone Camera)	4	4	100
Weaving 12 Exit	5	5	100

TABLE 4.3
The camera location and setting of the weaving areas

Weaving Area ID	Weaving Area Description	Entry Camera ID	Entry Camera Preset Number	Exit Camera ID	Exit Camera Preset Number
1	I-70 West Bound Post to I-465	90	7	88	7
2	I-70 East Bound I-465 to Post	88	6	90	6
3	I-465 North Bound I-70 to Pendleton Pike	143	6	41	6
4	I-265 East Bound I-65 to SR 62	326	6	344	6
5	I-265 West Bound SR 62 to I-65	344	7	326	7
6	I-69 North Bound 96th St to 106th St	202	6	204	6
7	I-69 South Bound 106th St to 96th St	204	7	202	7
8	I-69 South Bound 71st St to I-465	126	7	162	7
9	I-465 North Bound 71st St to 86th St	21	6	23	6
10	I-465 South Bound 86th St to 71st St	23	7	21	7
11	I-465/47.2 US 52 East, Brookville Rd.	Drone	–	47	–
12	I-70/88.7 Shadeland Ave	188	–	Drone	–

These results demonstrate the reliability of the system's vehicle counting.

There are two possible scenarios for vehicles that are not counted correctly: the system either double-counted a vehicle or missed the vehicle entirely. When the system double-counts a vehicle, it assigns two distinct IDs to the same vehicle. Consequently, this vehicle may be matched with two different vehicles since each unique ID is treated as a separate vehicle. When the system misses the vehicle, it cannot find a corresponding match. There may be instances where the system will try to guess a match, resulting in incorrect pairings. However, it is worth noting that the overall accuracy of the counting exceeds 90%, demonstrating the applicability and practicality of the developed vehicle counting method in traffic weaving areas.

4.4.3 Analysis of Vehicle Match Using Vehicle Features (Before Manual Check)

The AI-generated vehicle features are used to match the vehicles at the entry and exit of the weaving area. To describe the accuracy of the final vehicle matching results (before manual checking), we used the ground truth data obtained manually to obtain the true positive rate (TPR) and precision. TPR indicates the percentage of all potential matching vehicles the algorithm considered a match (not necessarily the actual match). Precision provides the percentage of the accurate match in all algorithm-considered matches. Table 4.4 shows the results of the experiment. It can be seen that the results of some weaving areas (e.g., 1, 11, and 12, shown in red color) are, in general, better than those of other weaving areas. The results of all other weaving areas are either low or inconsistent over time. Checking closely at these weaving areas, it can be concluded that the results are better when the cameras see the same side of the vehicles at both entry and exit. It is reasonable that the visual features of a vehicle seen from different sides are different; thus, the matching chance is lower. Therefore, getting the cameras to see the vehicles in the same direction at both entry and exit is advisable. For Weaving Area 2, although the cameras at the entry and exit see two different ends of the vehicle, they do see the same side of the vehicle, so the matching result is still usable sometimes.

4.4.4 Analysis of Vehicle Match After Manual Elimination of False Match

A certain number of pairs are false matches for all the matched vehicle pairs generated by the program. After the user visually checks and eliminates the false matches, the TPR will be decreased, but the precision will be 100%. Table 4.5 shows the precision of the vehicle match and the video quality. Table 4.6 shows the results after the manual elimination of false matches.

4.4.5 Presentation of Weaving Analysis Results

Figures 4.10 to 4.12 show the result of all cars, cars-only, and truck-only weaving analysis of Weaving Area 2 morning in a Sankey diagram, respectively.

TABLE 4.4
Comparison of counting accuracies between manual count and program count

Weaving Scenario and Location	Manual Count	Program Count	Accuracy (%)
Weaving 1 Entry Morning	93	100	93
Weaving 1 Exit Morning	104	100	104
Weaving 1 Entry Noon	98	100	98
Weaving 1 Exit Noon	97	100	97
Weaving 1 Entry Afternoon	100	100	100
Weaving 1 Exit Afternoon	96	100	96
Weaving 2 Entry Morning	100	100	100
Weaving 2 Exit Morning	94	100	94
Weaving 2 Entry Noon	100	100	100
Weaving 2 Exit Noon	96	100	96
Weaving 2 Entry Afternoon	100	100	100
Weaving 2 Exit Afternoon	91	100	91
Weaving 6 Entry Afternoon	94	100	94
Weaving 6 Exit Noon	99	100	99
Weaving 8 Entry Morning	93	100	93
Weaving 8 Exit Morning	84	100	84
Weaving 8 Entry Noon	91	100	91
Weaving 8 Exit Noon	81	100	81
Weaving 8 Entry Afternoon	94	100	94
Weaving 8 Exit Afternoon	83	100	83
Weaving 9 Entry Morning	98	100	98
Weaving 9 Exit Morning	100	100	100
Weaving 9 Entry Noon	100	100	100
Weaving 9 Exit Noon	97	100	97
Weaving 9 Entry Afternoon	95	100	95
Weaving 9 Exit Afternoon	100	100	100
Weaving 10 Entry Morning	102	100	102
Weaving 10 Exit Morning	100	100	60
Weaving 10 Entry Noon	100	100	100
Weaving 10 Exit Noon	100	100	100
Weaving 10 Entry Afternoon	100	100	100
Weaving 10 Exit Afternoon	100	100	100
Weaving 11 Entry (Drone Camera)	100	100	100
Weaving 11 Exit	100	100	100
Weaving 12 Entry (Drone Camera)	100	100	100
Weaving 12 Exit	100	100	100

TABLE 4.5
Experiment results show the TPR and precision before manually checking program-generated matches

Weaving Areas and Scenarios	(TP+FP)/Total Vehicles (%)	Precision (%)	Vehicle Viewing Angle	Video Quality
Weaving Area 1 Morning	44.36	67.69	Rear-Rear	Good-Good
Weaving Area 1 Noon	47.81	88.19	Rear-Rear	Good-Good
Weaving Area 1 Afternoon	41.18	74.83	Rear-Rear	Good-Good
Weaving Area 2 Morning	59.22	69.44	Front/Side-Rare/Side	Good-Good
Weaving Area 2 Noon	0	0	Front/Side-Rare/Side	Good-Poor
Weaving Area 2 Afternoon	53.89	64.04	Front/Side-Rare/Side	Good-Good
Weaving Area 6 Morning	38.51	42.60	Rear-Front	Good-Good
Weaving Area 6 Noon	41.22	46.54	Rear-Front	Good-Good
Weaving Area 6 Afternoon	3.86	12.40	Rear-Front	Good-Good
Weaving Area 8 Morning	0	0	Rear-Front	Poor-Poor
Weaving Area 8 Noon	0	0	Rear-Front	Poor-Poor
Weaving Area 8 Afternoon	0	0	Rear-Front	Poor-Poor
Weaving Area 9 Morning	42.54	43.24	Rear-Front	Good-Good
Weaving Area 9 Noon	55.10	31.96	Rear-Front	Good-Good
Weaving Area 9 Afternoon	53.04	29.66	Rear-Front	Good-Good
Weaving Area 10 Morning	3.80	25.00	Rear-Front	Good-Good
Weaving Area 10 Noon	10.31	54.54	Rear-Front	Good-Good
Weaving Area 10 Afternoon	9.43	4.60	Rear-Front	Good-Good
Weaving Area 11 (Entry Drone)	35.43	71.85	Front-Front	Good-Good
Weaving Area 12 (Exit Drone)	39.35	88.46	Front-Front	Good-Good

Note: Red results are, in general, better than those of other weaving areas.

TABLE 4.6
Experiment results show the TPR and precision after manually checking program-generated matches

Weaving Areas and Scenarios	TP/Total Vehicles (%)	Precision (%)	Vehicle Viewing Angle	Video Quality
Weaving Area 1 Morning	33.53	100	Rear-Rear	Good-Good
Weaving Area 1 Noon	42.38	100	Rear-Rear	Good-Good
Weaving Area 1 Afternoon	32.9	100	Rear-Rear	Good-Good
Weaving Area 2 Morning	45.36	100	Front/Side-Rare/Side	Good-Good
Weaving Area 2 Afternoon	39.64	100	Front/Side-Rare/Side	Good-Good
Weaving Area 11 (Entry Drone)	27.65	100	Front-Front	Good-Good
Weaving Area 12 (Exit Drone)	35.28	100	Front-Front	Good-Good

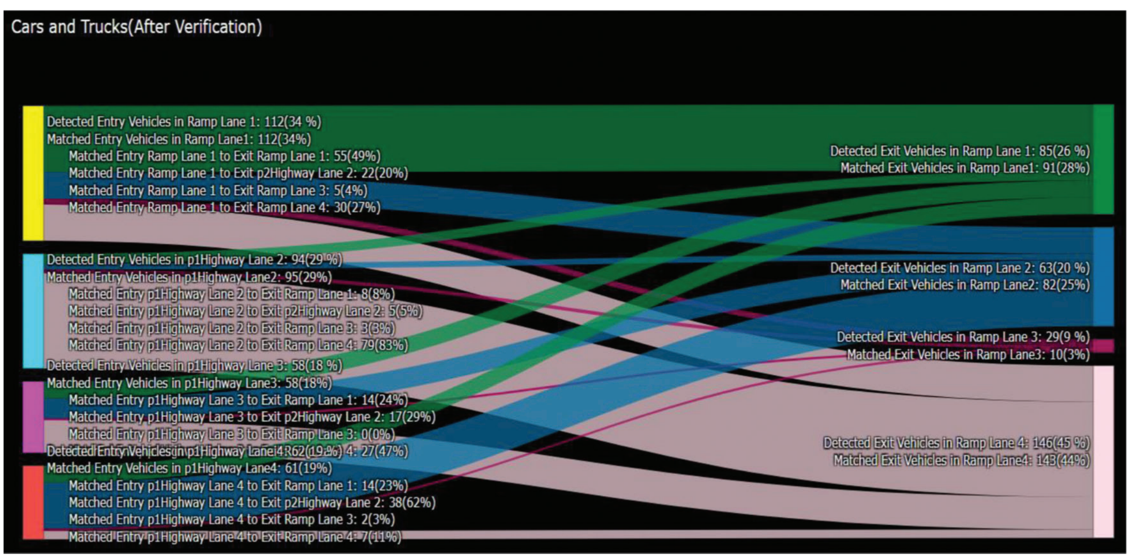

Figure 4.10 Sankey diagram for all vehicles after manual vehicle match verification.

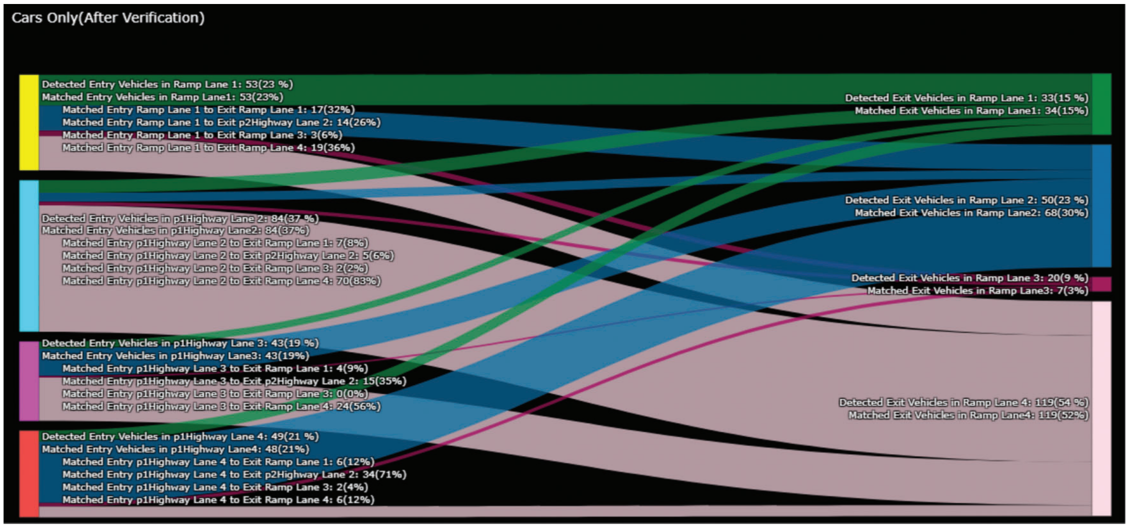

Figure 4.11 Sankey diagram for cars after manual vehicle match verification.

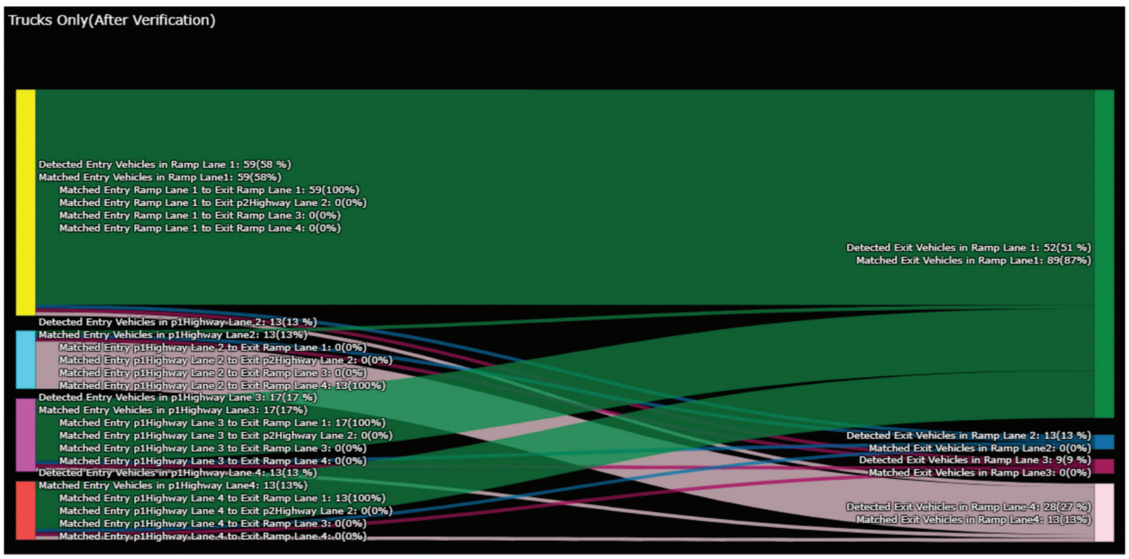

Figure 4.12 Sankey diagram for trucks after manual vehicle match verification.

5. PROJECT DELIVERY

The complete software, software installation manual, user manual, and camera setting guide document have been delivered to INDOT. The system has been implemented in INDOT. This project has been accepted for oral presentation in 2024 TRB in Washington, DC.

6. DISCUSSION

There are some limitations and potential solutions for applying this method.

1. The cameras at the weaving entry locations and the exit locations need to see the same sides of the vehicles. This ensures similar vehicle features of the vehicles can be seen at both entry and exit to achieve a certain matching accuracy. When the camera at the weaving entry and camera at the weaving exit see different sides of the vehicle (especially one sees only the front and other sees the rare), there are less common features generated, hence poor feature matching results. For a camera to see both entry ramp and highway, and the other camera to see exit ramp and highway in the same weaving area, the two cameras usually do not see the same side of the vehicles. One way to solve this problem is to use a drone at the weaving entry or exit. This solution has been tested and results are very good since the drone can take videos at better viewing location and angle than highway cameras. The limitation is that the flying time for a drone is limited (in our case, it is 45 minutes), so multiple drones are taking videos one after another when longer data taking time is needed.
2. Another limitation is that the highway camera should not be moved during weaving data collection. As the camera angle and zoom change, the road location on the video

changes, then the vehicle detected cannot match the lanes. However, for the weaving are being interested to do analysis, the traffic monitor operators are often interested in these areas and change the camera angle and zoom. Some coordination between the weaving data collector and the traffic management operators are needed.

7. CONCLUSION

A novel lane-based weaving analysis method was successfully developed. The method uses the advantages of AI algorithms for vehicle detection, tracking, and feature extraction to generate initial approximate results. Knowing the limitations of AI methods, the proposed method used filters based on physical constraints and reasoning to improve the results significantly. As there are no other ways to improve the result further, the user is asked to finally be involved to perfect the results. Since it is challenging to match all vehicles between the entry and exit, the matched vehicles in a weaving area are considered samples to obtain the final results of the weaving analysis. The proposed method has been implemented as a software tool and successfully tested using actual weaving area data. This software tool has been implemented in INDOT to improve highway traffic analysis and alternative development.

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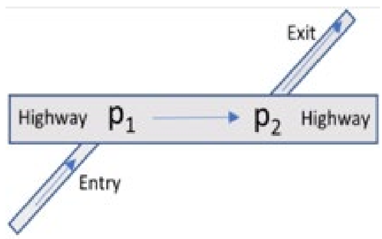
APPENDICES

Appendix A. Setting Up a Camera for Weaving Video Data Collection

APPENDIX A. SETTING UP A CAMERA FOR WEAVING VIDEO DATA COLLECTION

A.1 Background

Vehicle weaving between an exit ramp and an adjacent entry ramp is shown in Figure 1. To understand how the vehicles are weaving, we can use two cameras to record the video and then use the computer program to quantify how the vehicle weaving between the lanes from entry to the exit.



A.2 Camera Setup Steps

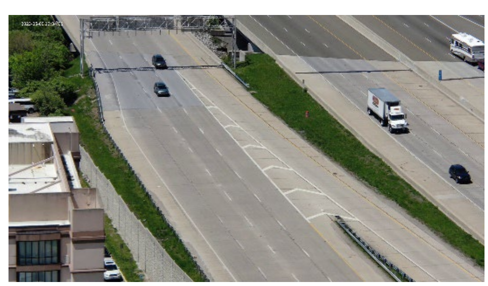
1. Number of cameras:
    a. Two cameras are needed: One is at the entry, and one is at the exit.

2. Camera setup
    a. Two camera's system times should be set up the same (within a few seconds). The videos should be recorded at the same time.
    b. Ensure the camera is set to record timestamps and show it on the video, which is critical for data analysis.
    c. If camera Focus and Exposure can be set, the camera's focus should be set to ensure clear, sharp images of the vehicles. Adjust the exposure settings to handle different lighting conditions during the day.
    d. If possible, set the camera to record at the highest resolution and frame rate it supports, as this will provide the most detailed and accurate data.

3. Camera location and viewing angle set up:
    a. Both cameras should be looking at the same side of the vehicle (either the top-front-side or the top-rear-side). See the following example.

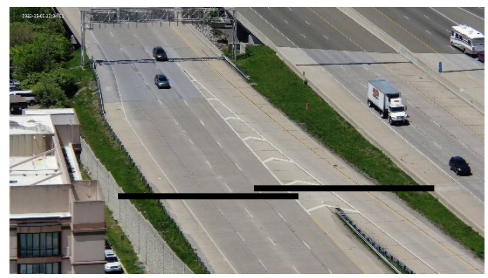
Entry camera

Exit camera

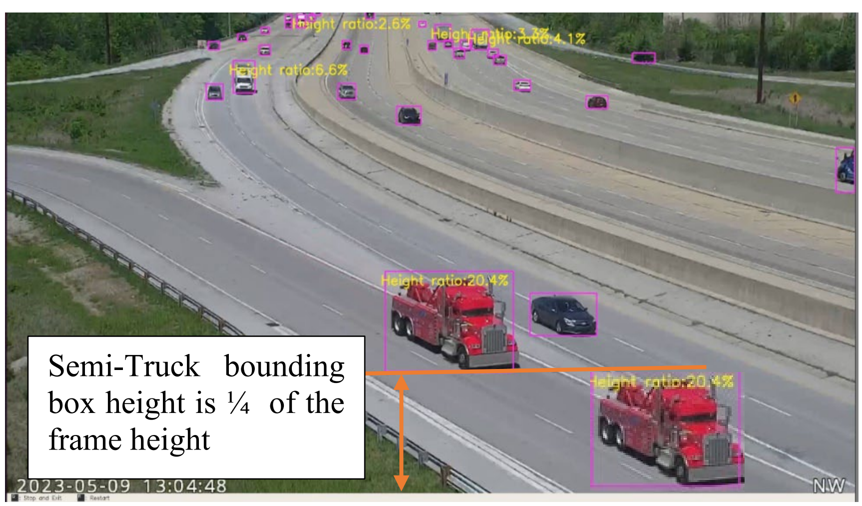


i. Two highway cameras usually cannot satisfy this requirement.
ii. One highway camera can be used first to determine which side of vehicles is seen. Then the drone camera can be set up to see the same side of the vehicles.
iii. Two drone cameras can be used to record simultaneously (one at entry and one at exit) if no highway camera exists at both entry and exit.

b. Determine a road location (at both entry and exit) where you want to detect and count vehicles. The ideal location is at the highway and ramp about to join (at entry) or split (at exit), but the highway and ramp are 2 to 5 lanes apart. Around that location, specify a horizontal line (we call it baseline) across the highway and another baseline across the ramp.



c. Adjust the camera angle and zoom level, and possibly the camera location to achieve the following.
i. The frame should clearly cover all lanes of the highway and ramp at the baseline.
ii. Assume there is a rectangle bounding box (aligned with the x and y axes of the frame) around all vehicles. Adjust the camera angle and zoom level to satisfy both of the following two conditions (1) the top of the semi-truck bounding box should be about $1/4^{th}$ of the whole frame height while the bottom of the semi-truck bounding box is at the bottom of the frame. (2) the baseline is at the about ¼ of the whole frame height from the bottom of the frame.



iii. Avoid any structure (e.g., trees, road signs, light poles) that blocks the view of the lanes one or two passenger cars length above and below the specified baseline.

d. Set the camera viewing angle and zoom level or distance (especially for drones) such that:

i. The best viewing angle is clearly seeing all vehicles top, side, and end (front or rear). This is achieved by adjusting the camera position and viewing angle.

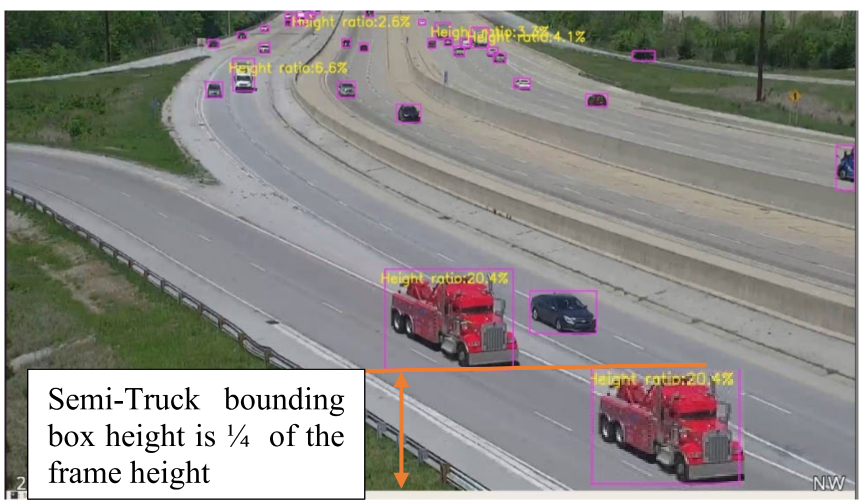
ii. Try to get a stable (not shaking) video with the sharpest vehicle image. Zooming in too much makes the image fuzzy and unstable. Windy weather makes a video shake and reduces the video quality. Nighttime/dark, raining, snowing conditions also reduce the video quality.

iii. Make sure any footage or caption does not cover the lanes below the baseline.

Note: Step 3 may need to be iterated to satisfy all requirements. Usually, drone camera has better freedom to be set, so begin by determining which fixed camera best meets the criteria above and use the drone at the other location.

A.3 Examples

Good Example: vehicle size is good all three sides are seen clearly.



A.4 Bad Examples of Baseline or Angle Settings

Bad viewing angle example 1 (see figure below): Vehicles on the ramp are easily occluded by vehicles on the highway lane.

Solution: If this is the highway camera, the freedom of camera motion is limited. The camera should be turned a little bit right and zoom in (red line). However, zoom in too much can cause image blur and shacking. If using a drone, the drone can fly higher to reduce occlusion.

Bad viewing angle example 2 (see figure below).
At this angle, we cannot see the side feature of the vehicle on the ramp well. It makes entry-exit vehicle matching difficult.

Suggested solution: If it is the highway camera, there is not much we can do because we cannot shift the camera left to see the side of vehicles. If it is a drone, move the drone to the left will enable the side of the vehicle visible.

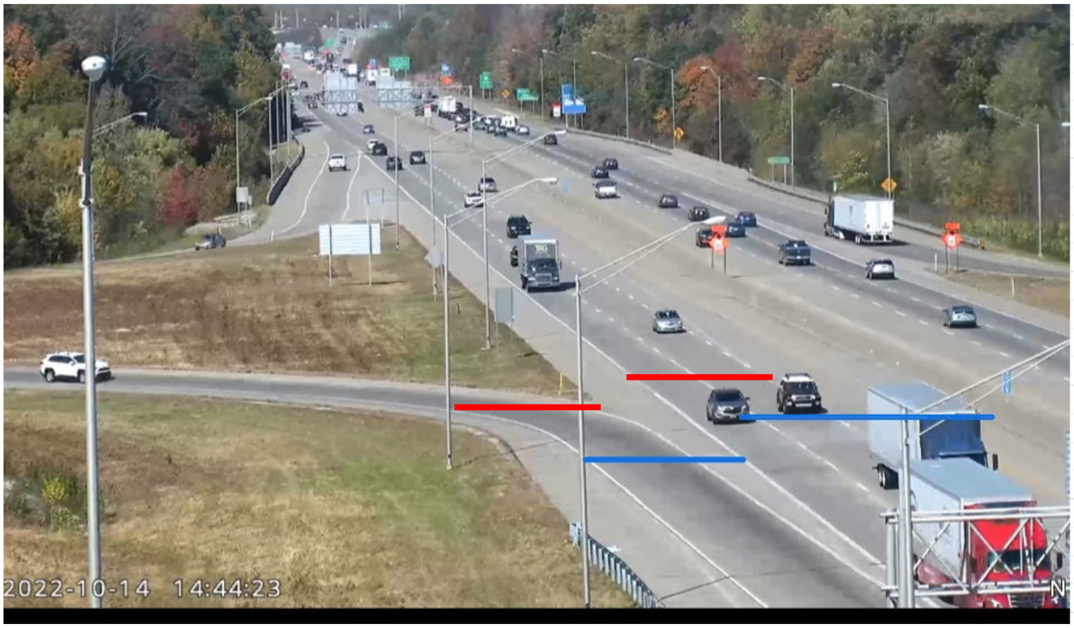
Bad example 3 of baseline selection (occlusion, see figure below).
1. Baseline is too close to the message board (pink circle), it will affect lane learning.
2. At this angle, we only see the front and top of the vehicles on the ramp so we cannot see the side feature of the vehicle. It makes entry-exit vehicle matching difficult.

The solution is to move down the baseline will improve the quality.

Bad example 4: Baseline too high on the frame. The clearer vehicle can be obtained if the camera angle can be adjusted higher, zoom in more, or make the drone get closer.

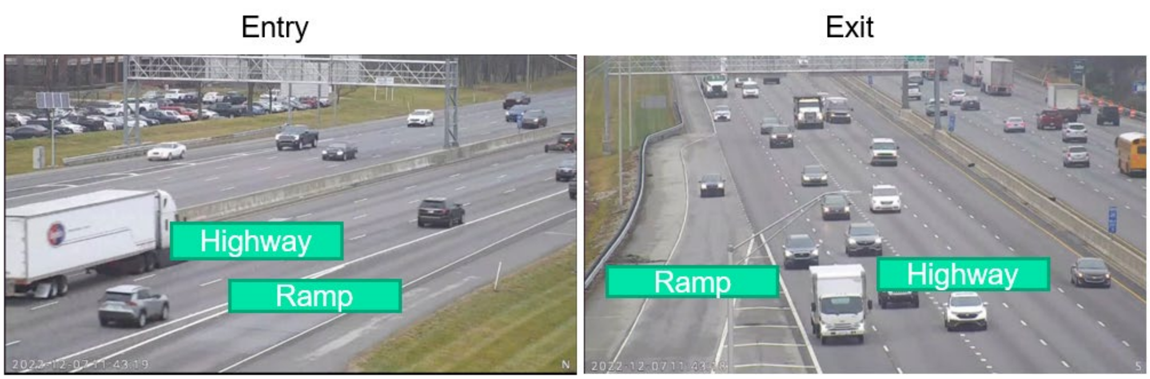
Solution: There is not an easy fix for this case. A better angle is to move the camera up and zoom in (see red line)

Bad example 5: Baseline too low and a fixed structure obscured the vehicles. So a large truck may not be detected at the baseline. Need to move the baseline higher and readjust he camera.



Solution: Move the baseline up and move the camera angle up.

Bad example 6: Entry and exit do not show the same sides of the vehicles.



Solution: Since entry camera provides a better view of the vehicles, need to use a drone at the exit to see the same sides of the vehicle.

About the Joint Transportation Research Program (JTRP)

On March 11, 1937, the Indiana Legislature passed an act which authorized the Indiana State Highway Commission to cooperate with and assist Purdue University in developing the best methods of improving and maintaining the highways of the state and the respective counties thereof. That collaborative effort was called the Joint Highway Research Project (JHRP). In 1997 the collaborative venture was renamed as the Joint Transportation Research Program (JTRP) to reflect the state and national efforts to integrate the management and operation of various transportation modes.

The first studies of JHRP were concerned with Test Road No. 1—evaluation of the weathering characteristics of stabilized materials. After World War II, the JHRP program grew substantially and was regularly producing technical reports. Over 1,600 technical reports are now available, published as part of the JHRP and subsequently JTRP collaborative venture between Purdue University and what is now the Indiana Department of Transportation.

Free online access to all reports is provided through a unique collaboration between JTRP and Purdue Libraries. These are available at http://docs.lib.purdue.edu/jtrp.

Further information about JTRP and its current research program is available at http://www.purdue.edu/jtrp.

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