Characterization of Continuous Trajectories for Deep ResNet Detected Vehicles and Manually Stitching of Unique IDs at "Gap" Locations

Gabriel Doty[1], Dr. Constantine Tarawneh[1], Dr. Alireza Talebpour[2]

[1]Department of Mechanical Engineering – The University of Texas Rio Grande Valley

[2]Department of Civil and Environmental Engineering – University of Illinois at Urbana-Champaign

U.S. Department of Transportation

The University of Texas Rio Grande Valley
Center for Multidisciplinary Research Excellence in Cyber-Physical Infrastructure Systems (MECIS)

1. Introduction

The US Department of Transportation's Federal Highway Administration started the Next Generation Simulation (NGSIM) and recently the Third Generation Simulation (TGSIM) data programs because there was a need to centralize and efficiently move forward research in traffic prediction, as well as in the advancements of autonomous vehicles. Even through this, there are numerous corners of the traffic prediction research communities that do not utilize their datasets in the best manner due to unidentified inaccuracies. One cause of these inaccuracies are due to "gap" locations. These impede a research team's time and effort.

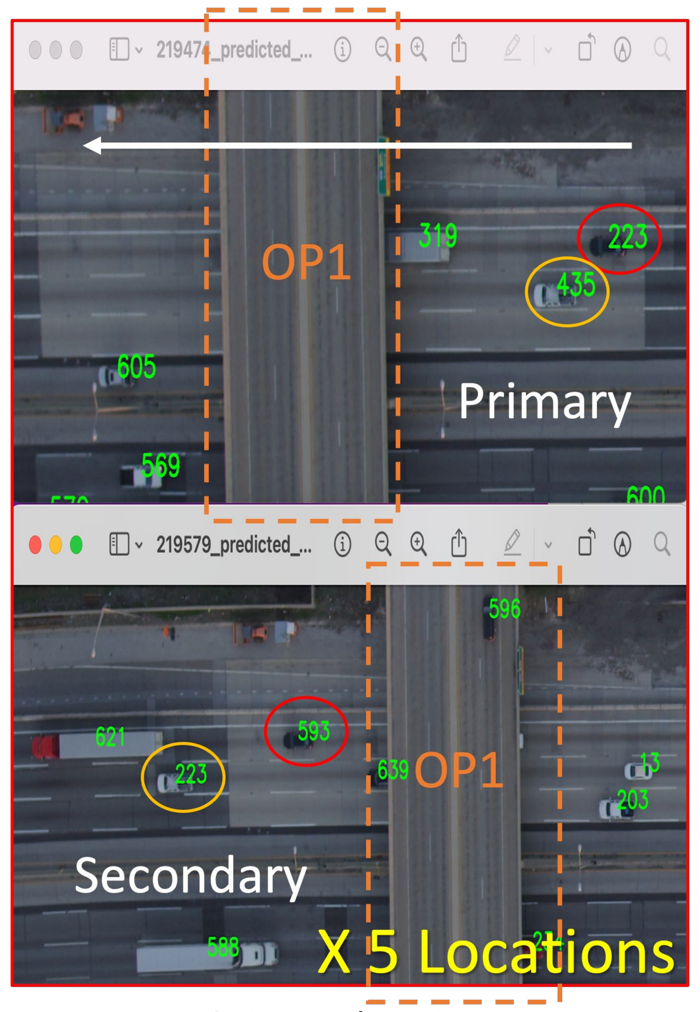

Fig. 1 Defining Primary & Secondary Segments. OP1 represents the first "gap" location. In the *global reference image*, there are 5 "gap" locations.

2. Purpose

Impact to USDOT Research Community				
Current Process	**Time**	**Future Process**	**Time**	**Potential Reduction**
1. Obtaining **individual** images using **4 codes**	2 weeks	1. Obtaining **batch** images using **1 code**	< 1 day	(~ 90% - 100% reduction)
2. Preprocessing of data **w/o characterization** of potential issues	2 months	2. Preprocessing of data **with characterization** of potential issues	2 weeks	(~ 50% reduction)
3. **Manually** "stitching" or matching unique IDs	1 month	3. **Automating process** for "stitching" or matching unique IDs	< 1 week	(~ 88% reduction)
4. **Manually processing data** for ALL (42) datasets in project	84 months (7 years)	4. **Processing data** for ALL (42) datasets in project **with automated process**	~ 2 months or less	(~ 98% reduction)
Overall Time Impact:	87.5 months		~ 3 months	(~ 97% reduction)

Fig. 2 Reduction in Time and Money for USDOT

Having a continuous/accurate dataset, along with the understanding of car-following and other microscopic behaviors that exist between vehicles, is critical to furthering the advancement of autonomous vehicles.

This is because "without empirical microscopic data, plausible but incorrect hypotheses perpetuate in the vacuum [1]."

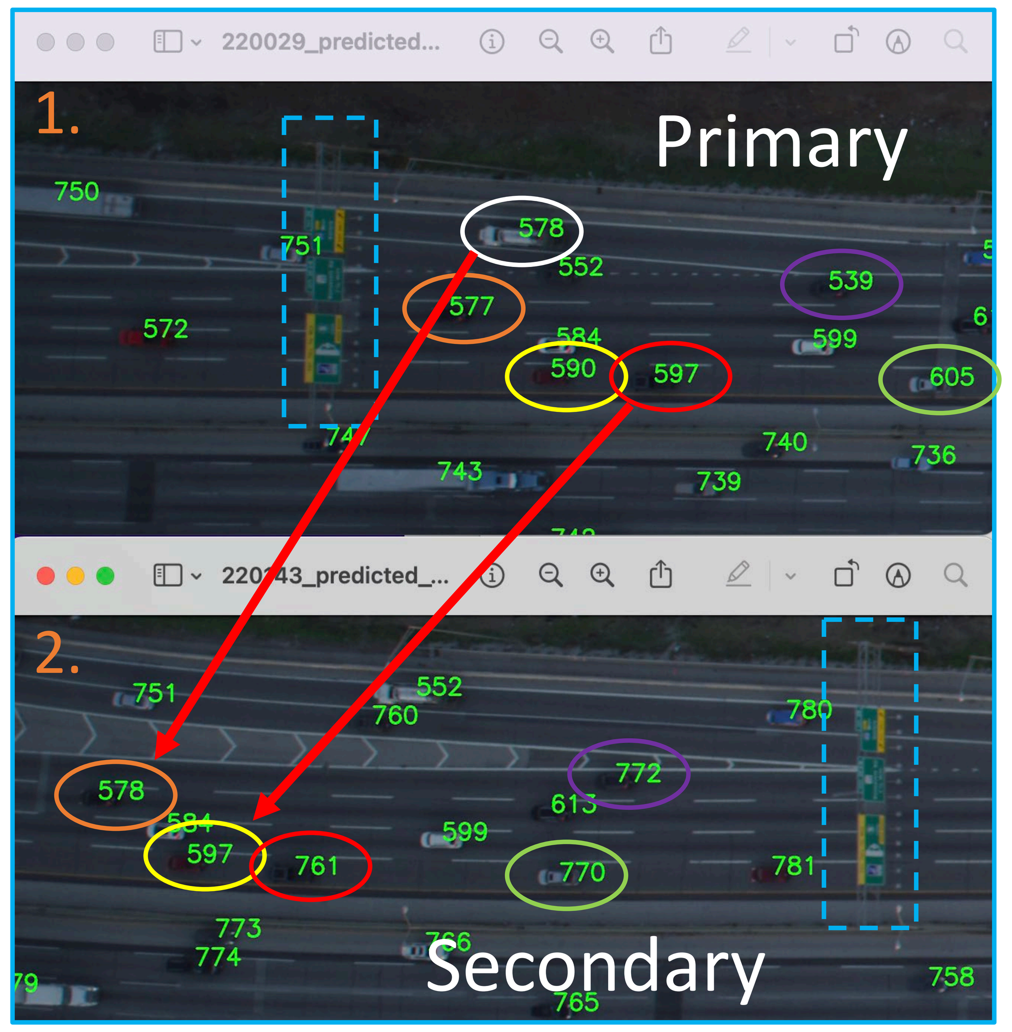

Fig. 3 Overhead sign "gap" issues: (1) Overhead sign causes an additional "gap" and causes "overused ID" issue; (2) also, vehicle could be given a new ID after passing under overpass or overhead sign and old ID is given to another vehicle. *(2 of 7 categories of issues identified – each issue occurs numerously)*

There are 5 "gap" locations in the *global reference image* that present issues where the Deep ResNet algorithm re-identifies vehicles, and these issues are prevalent through all 42 datasets. **Figure 2** outlines the overall time impact that my work would provide directly. As of right now, steps 2 and 3 in **Figure 2** are being done by 2 PhD students at the University of Illinois Urbana-Champaign. To account for the time needed **to accomplish this task manually, the cost incurred by the USDOT is approximately $8,000 – $12,000 annually, for a total cost of $56,000 - $84,000 over the course of 7.5 years. By automating this process, this would reduce the time to accomplish the same task significantly to around 3 months and could potentially save the USDOT $74,000.**

<u>Acronyms & Definitions</u>
OP: Overpass
NN: Neural Network
Global Reference Image – The Scale Invariant Feature Transformation (SIFT) algorithm was used for feature matching and image transformation to match local images to the global coordinates of the overall reference image. Manual image stitching and photoshop was used to obtain the overall reference image.
Filtering Code Equation – refers to the equation of motion used to apply a threshold to the data and filter the rest to match vehicle IDs from the primary segment to the secondary segment.
ResNet – ResNet algorithms use residual blocks w/ skipped connections to build deep NN without having gradients vanish or explode (as can be the case for deep networks).

3. Methodology

A large dataset consisting of vehicles traveling Northbound on I-90/I-94 in Chicago, IL was manually processed in stages 1-3 outlined in Figure 4. Then, the *filtering code equation* needs to be slightly adjusted to be robust enough to match vehicle IDs while considering uniquely captured characteristics (acceleration, velocity, time) at the particular "gap" location.

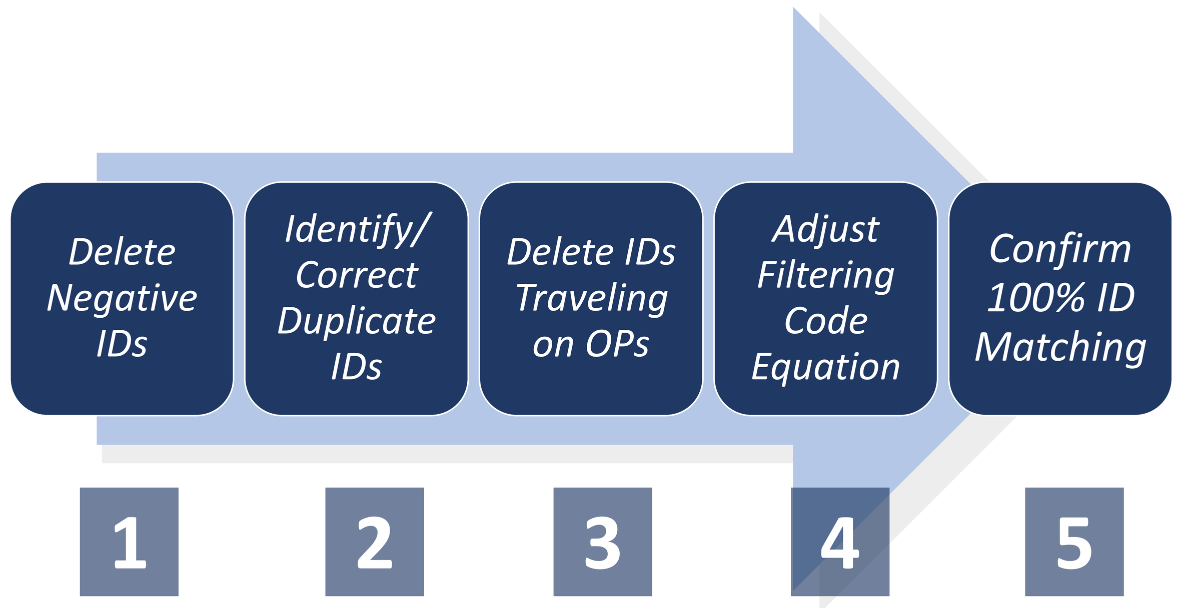

Fig. 4 Methodology for data preprocessing (1-3) & processing (4-5)

Other issues are captured simultaneously to provide for improved intuition. *Additional details about the filtering code and methodology can be found in the briefing folder.*

4. Results

After first stage of preprocessing of the data, the filtering code used for the first and second of three overpasses resulted in 100 percent accuracy of matching IDs from the *primary segment* to the *secondary segment*. More work needs to be done on the third overpass due to its size, angle, and traffic conditions at that particular segment of highway.

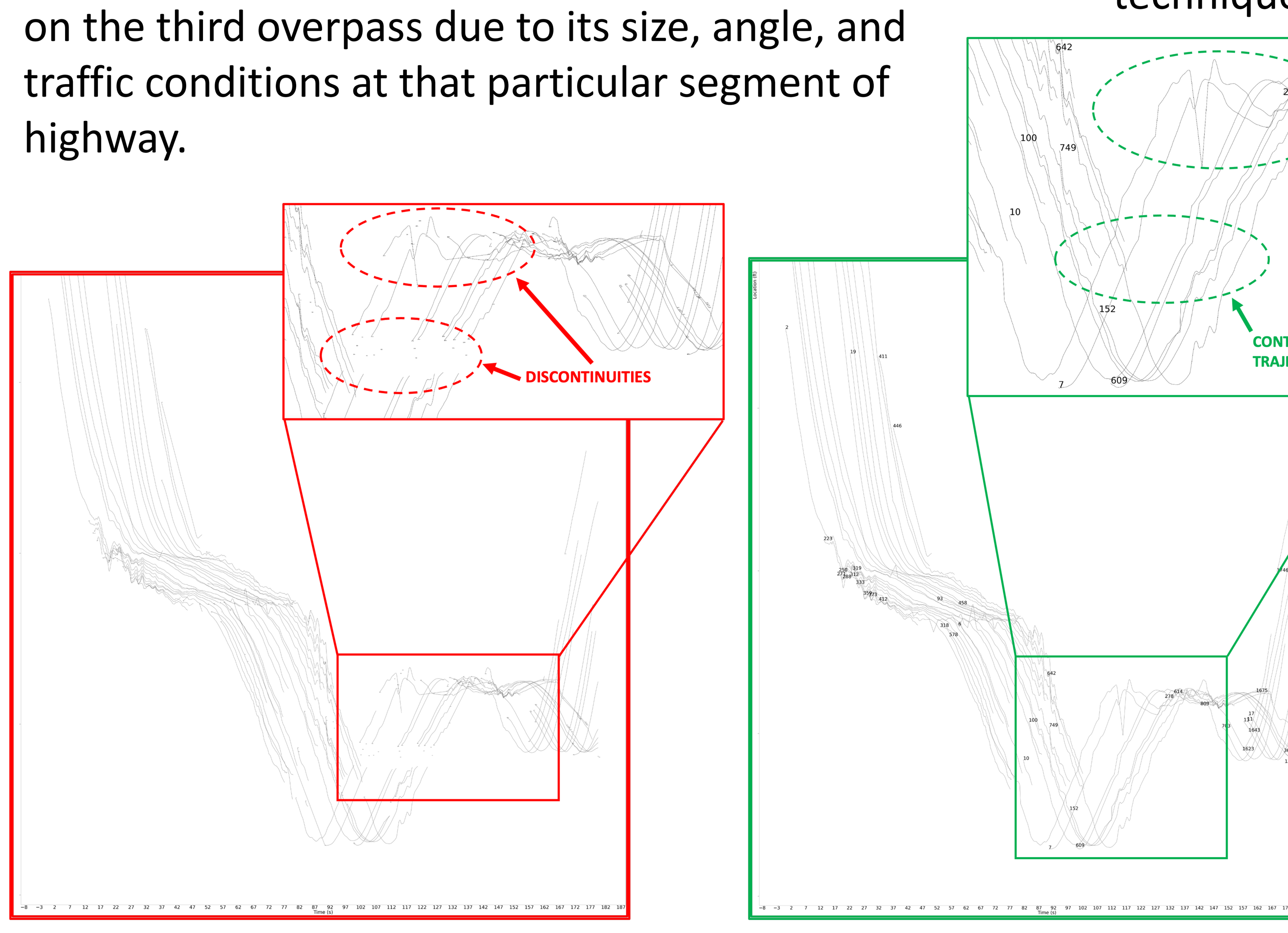

Fig. 5 "Gap" issue results in numerous unique IDs and discontinuities (L). Continuous trajectory result after manually matching all IDs for entire traveled trajectory (R).

The unique IDs were manually matched for the entire trajectory of the dataset used in this study. The manual matching of IDs took approximately one month to fully and correctly identify all vehicles' trajectories. As a result of manually matching IDs, the number of rows decreased from over 76,600 to under 75,850 and the number of unique IDs decreased 45% from 246 unique IDs to 111 unique IDs. *A "Master List of Matched IDs" can be found in the briefing folder.*

5. Conclusion & Future Work

Future Work Research Plan	
Task	**Time**
1. Reprocess original dataset (resulting in the initial inputs to compare versus the final targets)	3 weeks
2. Create code to obtain images in mass batches	1-2 week(s)
3. Edit filtering code to reduce redundancy & add additional logic	1 month
4. Apply machine learning on original initial inputs vs final targets	2 months
Total Time:	~ 4 months

Fig. 6 Methodology for data preprocessing (1-3) & processing (4-5)

Additional intuition was gained and therefore additional logic needs to be created and applied to strengthen the robustness of the *filtering code*. Location logic needs to be added to account for 2 additionally identified "gap" locations where overhead highway signs caused certain vehicles to receive new unique IDs. Once additional logic is created and applied successfully, machine learning techniques could be applied to automate the process and "stitch" the IDs together instead of filtering and matching IDs. There is limited research out there that has been tackling this issue.

6. Acknowledgement

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7. References

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