Validation of Freight Volume Modeling on Major Highway Links

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Project Objective

Validate the feasibility of leveraging the existing infrastructure and existing and emerging sensors, including repurposed sensors such as CCTV cameras and WIM stations, to estimate truck flow over a region of study situated north and east of the Ports of Los Angeles and Long Beach.

Problem Statement

One of the most challenging problems in urban transportation planning is the lack of fine-grain data on freight movements. Cities and regions do not know how many trucks operate in the area and have only limited information on freight flows. Without a consistent and current source for freight volume and origin-destination data, it is difficult to manage or plan for freight in metropolitan areas. This project aims to develop methods to generate freight volume information, e.g., estimate hourly origin-destination counts (OD-matrices), for different classes of trucks directly from sensor observations. Because data from sensors can be continuously updated in modern traffic information system networks, we could generate fine-grained truck flow estimates on historical data and in a close to real-time fashion.

Research Methodology

We focus on the highway system in an area of study we refer to as the region of interest (ROI), which covers approximately 12 square miles around the Ports of Los Angeles and Long Beach. This area was specifically selected because of the relatively high volume of trucks traveling in the region, which allows for many observations from the data sources available. The ROI contains many currently available sensors, including WIM, TAMS, and CCTV cameras. We worked with Caltrans and UCI to collect and store these sensor data. We develop a machine learning model to detect and count trucks and produce observations from CCTV cameras. We further formalize the problem of probabilistic truck localization to establish a Vehicle Detection Model that, given a set of sensor characteristics (e.g., reliability) and probabilistic vehicle detections, predicts the truck's current location and outputs a probability distribution of the truck's location. For this, we propose a new "Probabilistic Bridgelets" approach [4], which extends our prior work on Time-variant Road Network Bridgelets [5] to allow the generation of OD Matrices.

Results

Results include (i) a curated *Truck Sensing Dataset* containing sensor data in the ROI that other transportation researchers can leverage, (ii) state-of-the-art Truck Detection and Counting models specifically trained and tested on CCTVs in the ROI, and feasibility analysis of truck detection and counting on the real-world data of the *Truck Sensing Dataset*, and (iii) a novel Probabilistic Bridgelets approach for truck flow estimation, together with a feasibility analysis of truck flow estimation on the *Truck Sensing Dataset* data.

Truck Sensing Dataset We worked with Caltrans District 7 to collect CCTV cameras, with the California Department of Transportation Traffic Operations Weigh-in-Motion to collect WIM station data, and with UCI Institute of Transportation Studies to collect Truck Activity Monitoring

System (TAMS) data. The map and table below provide an overview of the sensors available in the ROI. Overlapping CCTV, WIM, and TAMS are available for Fri 11/3, 5 PM to Sun 11/5, 12 AM (19 hours) and Tue 11/7, 9 AM to Wed 11/8, 10 AM (13 hours). The dataset is made available to transportation researchers.

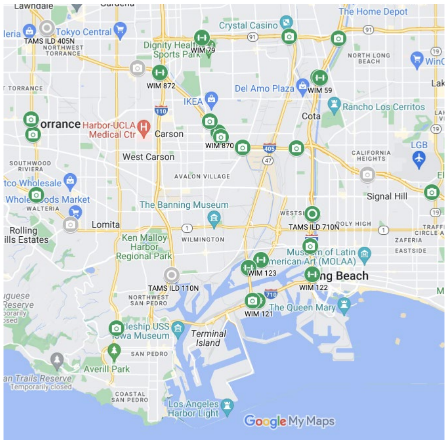

Figure 1: CCTV (cameras), WIM (weights), and TAMS (O) in ROI

Sensor	Periods Available	Count
CCTV	2023 11/02 5 PM to 11/05 12 AM 2023 11/07 9 AM to 11/08 10 AM	9
WIM	01/01/2019 – 08/31/2023 11/02/2023 – 11/08/2023	14
TAMS	11/01/2023 - 11/10/2023	2

Table 1: Sensors available in ROI

CCTV Truck Detection and Counting Modeling

This study aims to investigate the feasibility and usefulness of using traffic monitoring CCTV videos for truck detection and counting. Using a deep learning-based algorithm, i.e., YOLO, as the detection model, we explore the possible benefits of visual images in monitoring truck movement. To assess the effectiveness of our approach, truck traffic data were collected and labeled, encompassing both daytime and nighttime, employing our custom dataset sourced from Caltrans. Using the collected dataset, the performances of deep learning models trained for nighttime and daytime conditions were assessed and compared.

CCTV Truck Detection and Counting Feasibility Analysis

To generate inference results, we used 10 1-minute CCTV videos shot at location 255 between ~ 9:01-9:11 am. The 10 videos are stitched together to generate one, 10-minute 8-second long video. Mean average precision detection accuracy using an Intersection-over-Union (IoU) threshold of 0.5 was 0.786, 0.777 and 0.758, absolute difference between detected and actual normalized by actual number of trucks was 0.0967, 0.8 and 0.2857.

Truck Volume Modeling

Because CCTV and WIM sensors do not uniquely identify and track vehicles, extracting mobility patterns from their detections is challenging. We have proposed the VPE, which is short for Visit Probability Estimation. This framework processes roadside sensor observations to estimate the probability that a vehicle visits a road segment at a specific time. VPE is powered by LEM, short for Location Estimation Model, a novel mathematical model that calculates location transition probabilities while considering the sensors' reliability, and APD+, an algorithm that captures the uncertainty of movement between two endpoints. Our experiments on synthetic datasets show that the proposed methods achieve high accuracy while maintaining practical computation time.

Truck Volume Modeling Feasibility Analysis

We applied our proposed framework, VPE, to several realistically synthesized datasets of roadside sensor observations. In our simulations, our methods were able to estimate visit probabilities accurately. Specifically, the mean Jensen-Shannon divergence between the estimated and actual (simulated) distribution was approximately 5%, while the mean F1 score was approximately 40%.