Luciano Nocera\textsuperscript{1}, Gen Giuliano\textsuperscript{2}, Seon Ho Kim\textsuperscript{1} and Cyrus Shahabi\textsuperscript{1}
Chrysovalantis Anastasiou\textsuperscript{1}, Mustafa Alturki\textsuperscript{1}
Yiqing Fan\textsuperscript{1}, Yingzhe Liu\textsuperscript{1}, Luke Nelson\textsuperscript{1}, Aditi Hoskere Deepak\textsuperscript{1}

\textsuperscript{1} Integrated Media Systems Center (IMSC)
\textsuperscript{2} METRANS Transportation Consortium

FREIGHT MODELING RESEARCH
Need for more freight trucking data in SC

Freight trucking impacts:

- **Infrastructure:** maintaining roadways, adding charging stations, ...

- **Traffic:** planning to limit traffic and accidents that may cause, understand the economic impact, ...

- **Health:** understand the health impacts, transition to less polluting technologies, ...
Very limited freight data for SC

- Little information on trucks origin and destination (OD-matrix)
- Existing data is indirectly sourced from surveys at ports, warehouses, rail stations... leads to low temporal and spatial resolution OD-matrix

Current OD-matrix estimates at a time resolution not always compatible with what is needed for urban planning and assessing truck impact on traffic and AQ
Region of Study
What vehicles to consider

Federal Highway Administration Vehicle Classification
Sources of truck information currently available

Precise but sparse truck sensors:
- WIM (5), TAMS (6), RFID,
- Caltrans vehicle counting

Sensors used for other applications:
- CCTV (15) (monitoring)
- ILD (traffic, e.g., ADMS)
Freight Modeling From Sensor Data

**Goal:** provide high temporal and spatial resolution truck information
- OD-matrix
- Link-level volume

**Approach:** integrate truck sensors observations

**Some questions we want to answer:**
- How to estimate OD-Matrix from sensor observations?
- How accurate can we model flow? For example, how many sensors and what sensor layout is needed to obtain useful estimates?
- Can we use CCTV cameras? For example, can we utilize Caltrans’ CCTV monitoring cameras to classify & count trucks?
OD-matrix from surveys

\[ n_i^j: \text{count of trucks for class } (a, b, c, \ldots) \text{ over a period of time} \]

- \( i = 0 \) at Origin
- \( i = A \) at Destination A
- \( i = B \) at Destination B
OD-matrix from sensors observations

$t_{ij}^j, c_{ij}^j$: truck observation $i$ at sensor $j$
$t$: time of observation
$c$: truck class of observation
Approach: reconcile observations across sensors based on estimated travel times

$t_i^j$: truck $i$ time at sensor $j$

Travel times on links estimated from traffic sensors
Taking into account sensor data uncertainty for truck class, travel time and missing data

Traffic

Fast  |  |  Slow

Monday, 9:35 AM

8:00 AM 12:00 PM 4:00 PM 8:00 PM

S M T W T F S
Approaches we have developed

Baseline:
• Estimates flow only at road segments where data is sensed

Rule Flow:
• Extends estimation to adjacent edges as long as there is no road fork

Reach Flow:
• Finds compatible observations between sensors and imputes the flow on the edges of the shortest path between the sensors.
  • Observations are compatible if travel time is \([\text{approximately}]\) equal to their timestamp difference and detected truck type is the same
Validation of Freight Modeling

Challenges:

• No data was available last year with COVID-19 pandemic
• Lack of ground truth data (truck counts) for validation

Therefore:

• We built a truck simulator that uses historical traffic to simulate trajectories under different conditions
• Scraped Caltrans CCTV footage from off available webcams
Truck Simulator applied to Flow Modeling Validation

Real World Traffic (ADMS) → Truck Simulator → Simulated Truck Fleet Observations

Road Network
Sensors
Truck Fleet Initial Conditions & Destinations

Simulated Truck Fleet Trajectories
Simulated OD-Matrices
Simulated Volume on Links

Estimated OD-Matrices
Estimated Volume on Links

Truck Flow Model
Volume on links OD-Matrices
Truck Flow Modeling Results

Varying number of sensors (trucks = 1000)

- Low impact on precision with enough sensors

Varying number of trucks (sensors = 300)

- High recall

Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE)
Simulator dashboard

Truck simulation main screen

Truck simulations listing screen

Freight volume results comparison screen
Caltrans Web Cams

Together Too Far
≠ truck types
Front & back
Hard to see axels

Commercial van?

Occlusions Too far

Partially seen

Too Far

Different angles of view
CCTV Detection and Classification on Single Frames

What Truck classes to consider?

Axle-based US DOT vehicle classes

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>Motorcycles</td>
</tr>
<tr>
<td>Class 2</td>
<td>Passenger cars</td>
</tr>
<tr>
<td>Class 3</td>
<td>Four tons, single unit</td>
</tr>
<tr>
<td>Class 4</td>
<td>Buses</td>
</tr>
<tr>
<td>Class 5</td>
<td>Two axle, six tons, single unit</td>
</tr>
<tr>
<td>Class 6</td>
<td>Three axle, single unit</td>
</tr>
<tr>
<td>Class 7</td>
<td>Four or more axle, single unit</td>
</tr>
<tr>
<td>Class 8</td>
<td>Four or less axle, single trailer</td>
</tr>
<tr>
<td>Class 9</td>
<td>5-Axle tractor semitrailer</td>
</tr>
<tr>
<td>Class 10</td>
<td>Six or more axle, single trailer</td>
</tr>
<tr>
<td>Class 11</td>
<td>Five or less axle, multi trailer</td>
</tr>
<tr>
<td>Class 12</td>
<td>Six axle, multi-trailer</td>
</tr>
<tr>
<td>Class 13</td>
<td>Seven or more axle, multi-trailer</td>
</tr>
</tbody>
</table>

Existing image datasets vehicle classes

MIO-TCD dataset

---

Three Tiers, Size-based Classes

- **Small (Light-weight)**
  - DoT Class 5

- **Medium (Heavy-duty non articulated)**
  - DoT Class 6-7

- **Heavy (Heavy-duty articulated)**
  - DoT Class 8-13
Optimized Classes for Truck Classification

- **Van**
  - DoT Class 3, 5

- **Pickup**
  - DoT Class 3, 5

- **Single Unit**
  - DoT Class 6-10

- **Heavy-duty Articulated**
  - DoT Class 8-13
Dataset v2
Classes: lightweight single_unit_truck articulated_truck

Dataset v3
Classes: pickup single_unit_truck articulated_truck

Dataset v4
Classes: annotations: pickup_rear articulated_truck_front articulated_truck_rear
## Classification Results

### Dataset v-2 performance results

<table>
<thead>
<tr>
<th>confidence_threshold = 0.25</th>
</tr>
</thead>
<tbody>
<tr>
<td>articulated_truck, AP = 86.02% (TP = 84, FP = 21)</td>
</tr>
<tr>
<td>single_unit_truck, AP = 84.20% (TP = 76, FP = 33)</td>
</tr>
<tr>
<td>lightweight, AP = 63.00% (TP = 56, FP = 44)</td>
</tr>
<tr>
<td>Precision = 0.69 / Recall = 0.77 / F1-score = 0.73</td>
</tr>
<tr>
<td>TP = 216, FP = 98, FN = 65, Average IoU = 55.63 %</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>confidence_threshold = 0.50</th>
</tr>
</thead>
<tbody>
<tr>
<td>articulated_truck, AP = 86.02% (TP = 75, FP = 11)</td>
</tr>
<tr>
<td>single_unit_truck, AP = 84.20% (TP = 74, FP = 18)</td>
</tr>
<tr>
<td>lightweight, AP = 63.00% (TP = 51, FP = 22)</td>
</tr>
<tr>
<td>Precision = 0.88 / Recall = 0.71 / F1-score = 0.75</td>
</tr>
<tr>
<td>TP = 280, FP = 51, FN = 81, Average IoU = 64.57 %</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>mAP@0.50 = 0.777391, or 77.74 %</th>
</tr>
</thead>
<tbody>
<tr>
<td>mAP@0.60 = 0.731565, or 73.16 %</td>
</tr>
<tr>
<td>mAP@0.70 = 0.625322, or 62.53 %</td>
</tr>
<tr>
<td>mAP@0.80 = 0.357104, or 35.71 %</td>
</tr>
<tr>
<td>mAP@0.90 = 0.025788, or 2.58 %</td>
</tr>
</tbody>
</table>

### Dataset v-3 performance results

<table>
<thead>
<tr>
<th>confidence_threshold = 0.25</th>
</tr>
</thead>
<tbody>
<tr>
<td>articulated_truck, AP = 86.13% (TP = 88, FP = 27)</td>
</tr>
<tr>
<td>single_unit_truck, AP = 84.87% (TP = 76, FP = 31)</td>
</tr>
<tr>
<td>van, AP = 49.90% (TP = 13, FP = 8)</td>
</tr>
<tr>
<td>pickup, AP = 76.33% (TP = 46, FP = 30)</td>
</tr>
<tr>
<td>Precision = 0.70 / Recall = 0.79 / F1-score = 0.74</td>
</tr>
<tr>
<td>TP = 223, FP = 96, FN = 58, average IoU = 56.48 %</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>confidence_threshold = 0.50</th>
</tr>
</thead>
<tbody>
<tr>
<td>articulated_truck, AP = 86.13% (TP = 83, FP = 18)</td>
</tr>
<tr>
<td>single_unit_truck, AP = 84.87% (TP = 72, FP = 22)</td>
</tr>
<tr>
<td>van, AP = 49.90% (TP = 12, FP = 6)</td>
</tr>
<tr>
<td>pickup, AP = 76.33% (TP = 41, FP = 16)</td>
</tr>
<tr>
<td>Precision = 0.77 / Recall = 0.74 / F1-score = 0.75</td>
</tr>
<tr>
<td>TP = 248, FP = 62, FN = 73, average IoU = 62.45 %</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>mAP@0.50 = 0.743074, or 74.31 %</th>
</tr>
</thead>
<tbody>
<tr>
<td>mAP@0.60 = 0.705981, or 70.59 %</td>
</tr>
<tr>
<td>mAP@0.70 = 0.614802, or 61.48 %</td>
</tr>
<tr>
<td>mAP@0.80 = 0.352933, or 35.29 %</td>
</tr>
<tr>
<td>mAP@0.90 = 0.035619, or 3.56 %</td>
</tr>
</tbody>
</table>
Classification Results

**Dataset v-3 performance results**

- confidence_threshold = 0.25
  - articulated_truck, AP = 86.13% (TP = 88, FP = 27)
  - single_unit_truck, AP = 84.87% (TP = 75, FP = 31)
  - van, AP = 49.90% (TP = 13, FP = 8)
  - pickup, AP = 76.33% (TP = 45, FP = 39)

  Precision = 0.70 / Recall = 0.79 / F1-score = 0.74
  TP = 223, FP = 95, FN = 58, average IoU = 55.40%

- confidence_threshold = 0.50
  - articulated_truck, AP = 86.13% (TP = 83, FP = 18)
  - single_unit_truck, AP = 84.87% (TP = 72, FP = 22)
  - van, AP = 49.90% (TP = 12, FP = 8)
  - pickup, AP = 76.33% (TP = 41, FP = 10)

  Precision = 0.77 / Recall = 0.74 / F1-score = 0.75
  TP = 208, FP = 62, FN = 73, average IoU = 62.45%

**Dataset v-4 performance results**

- confidence_threshold = 0.25
  - articulated_truck_front, AP = 90.93% (TP = 61, FP = 23)
  - articulated_truck_rear, AP = 84.24% (TP = 29, FP = 12)
  - single_unit_truck_front, AP = 78.12% (TP = 37, FP = 11)
  - single_unit_truck_rear, AP = 84.53% (TP = 36, FP = 16)
  - van_front, AP = 38.44% (TP = 7, FP = 1)
  - van_rear, AP = 59.75% (TP = 3, FP = 4)
  - pickup_front, AP = 66.82% (TP = 16, FP = 12)
  - pickup_rear, AP = 69.27% (TP = 23, FP = 7)

  Precision = 0.69 / Recall = 0.76 / F1-score = 0.72
  TP = 214, FP = 97, FN = 67, average IoU = 56.09%

- confidence_threshold = 0.50
  - articulated_truck_front, AP = 90.93% (TP = 60, FP = 17)
  - articulated_truck_rear, AP = 84.24% (TP = 26, FP = 5)
  - single_unit_truck_front, AP = 78.12% (TP = 33, FP = 11)
  - single_unit_truck_rear, AP = 84.53% (TP = 34, FP = 11)
  - van_front, AP = 38.44% (TP = 6, FP = 6)
  - van_rear, AP = 59.75% (TP = 3, FP = 4)
  - pickup_front, AP = 66.82% (TP = 14, FP = 5)
  - pickup_rear, AP = 69.27% (TP = 23, FP = 6)

  Precision = 0.75 / Recall = 0.71 / F1-score = 0.73
  TP = 119, FP = 65, FN = 82, average IoU = 61.76%
# Image datasets

<table>
<thead>
<tr>
<th></th>
<th>v2</th>
<th>v3</th>
<th>v4</th>
</tr>
</thead>
<tbody>
<tr>
<td># of images</td>
<td>1253</td>
<td>1253</td>
<td>1253</td>
</tr>
<tr>
<td># of background images</td>
<td>300</td>
<td>300</td>
<td>300</td>
</tr>
<tr>
<td>Total # of images</td>
<td>1553</td>
<td>1553</td>
<td>1553</td>
</tr>
<tr>
<td>articulated_truck count</td>
<td>1029</td>
<td>1029</td>
<td></td>
</tr>
<tr>
<td>articulated_truck_front count</td>
<td></td>
<td></td>
<td>634</td>
</tr>
<tr>
<td>articulated_truck_rear count</td>
<td></td>
<td></td>
<td>395</td>
</tr>
<tr>
<td>single_unit_truck count</td>
<td>922</td>
<td>922</td>
<td></td>
</tr>
<tr>
<td>single_unit_truck_front count</td>
<td></td>
<td></td>
<td>501</td>
</tr>
<tr>
<td>single_unit_truck_rear count</td>
<td></td>
<td></td>
<td>421</td>
</tr>
<tr>
<td>lightweight count</td>
<td>866</td>
<td></td>
<td></td>
</tr>
<tr>
<td>van count</td>
<td></td>
<td>225</td>
<td></td>
</tr>
<tr>
<td>van_front count</td>
<td></td>
<td></td>
<td>128</td>
</tr>
<tr>
<td>van_rear count</td>
<td></td>
<td></td>
<td>97</td>
</tr>
<tr>
<td>pickup count</td>
<td></td>
<td>641</td>
<td></td>
</tr>
<tr>
<td>pickup_front count</td>
<td></td>
<td></td>
<td>253</td>
</tr>
<tr>
<td>pickup_rear count</td>
<td></td>
<td></td>
<td>388</td>
</tr>
</tbody>
</table>
Future Work: using tracking on videos

