Roadway Traffic Flow Estimation using Video Imagery Data Collected from Transit Bus Cameras

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The Ohio State University

TransitData 2019 Workshop and Symposium

Paris, France
July 7-11, 2019
Objective

Develop and demonstrate an approach to estimate roadway traffic flows across extensive urban roadway networks using video imagery collected from transit buses.
Motivation

• Traditional roadway traffic studies typically involve observations at stationary locations
• A few locations are observed over fairly long time periods (hours or days)
Motivation, cont.

- Transit buses cover major areas (routes) in roadway network regularly
- Most are equipped with video cameras for security and liability purposes

Part of OSU Campus Area Bus Service (CABS) route map
Concept
Concept

• Take advantage of existing video imagery
• Take advantage of existing video imagery
• Estimate roadway traffic flow from repeated observations
Study Design

• Collect data
  – Video imagery (to estimate roadway traffic flows)
  – Road tube counts (“ground truth” to validate results)
• Extract vehicle locations and time-stamps from video imagery
• Modify moving observer method to estimate traffic flows from extracted vehicle data
• Apply modified method to estimate traffic flows
• Validate estimates
  – Qualitatively
  – Quantitatively
Data and Network

• Road tube counts
  – 24-hour 15-minute bidirectional traffic counts on 5 segments in Oct. 25, 2019
  – “Ground truth” (recognizing that counts are subject to measurement errors)
Data and Network

- **Road tube counts**
  - 24-hour 15-minute bidirectional traffic counts on 5 segments in Oct. 25, 2019
  - “Ground truth” (recognizing that counts are subject to measurement errors)

- **Video imagery**
  - Estimate roadway traffic flows
Video Imagery

- Video imagery used
  - Side-view camera
  - Down-sampled to 10 FPS
  - 12-hour footage on 5 buses between 7AM to 7PM on October 25, 2019
  - 1 CLN, 2 CLS, and 2 WC buses
  - Total of 60 video-hours

<table>
<thead>
<tr>
<th>Route</th>
<th>7AM - 11AM</th>
<th>11AM - 3PM</th>
<th>3PM - 7PM</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLN</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>12</td>
</tr>
<tr>
<td>CLS</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>24</td>
</tr>
<tr>
<td>WC</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>24</td>
</tr>
<tr>
<td>Total</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>60</td>
</tr>
</tbody>
</table>

Available (video-hours)

July 8, 2019

The Ohio State University
Extract Vehicle Information from Video Imagery

• Developed (in MATLAB) a video-based vehicle Counting GUI
• Semi-automatically identified and recorded vehicle locations and times using human processors
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Traditional Moving Observer Traffic Flow Estimation Method

• Observer travels in both directions 1 and 2 of roadway segment during a homogeneous time period
• Count vehicles in opposite direction while traversing direction 1
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\[ q = \frac{\text{dir.1} n_{veh} + \cdots}{t_1 + \cdots} \]
Traditional Moving Observer Traffic Flow Estimation Method

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- Count vehicles in opposite direction while traversing direction 1

\[ q = \frac{\text{dir.1} \cdot \text{n.veh} + \ldots}{t_1 + \ldots} \]

- Count vehicles overtaking observer and being overtaken by observer in same direction while traversing direction 2
Traditional Moving Observer Traffic Flow Estimation Method

• Observer travels in both directions 1 and 2 of roadway segment during a homogeneous time period

• Count vehicles in opposite direction while traversing direction 1

\[
q = \frac{\text{dir.}1 n_{\text{veh}} + \ldots}{t_1 + \ldots}
\]

• Count vehicles overtaking observer and being overtaken by observer in same direction while traversing direction 2

\[
q = \frac{\text{dir.}1 n_{\text{veh}} + (\text{dir.}2 n_{\text{veh}}^{\text{overtaking}} - \text{dir.}2 n_{\text{veh}}^{\text{overtaken}})}{t_1 + t_2}
\]
Traditional Moving Observer Traffic Flow Estimation Method, cont.

• Limitations of traditional moving observer method
  - Impractical for observer to traverse both directions during a homogeneous time period
  - Inability to take advantage of transit buses that either do not traverse both directions or are not available to traverse direction 2 in a timely manner
  - Inability to observe traffic continuously between contiguous segment-directions

• Need to modify the method for one-directional observations to either resolve or negate these limitations
Modified Moving Observer Traffic Flow Estimation Method

• Traverse segment in one direction (1) only

• Assume travel time of virtual traversal in other direction (2)

• \( q = \frac{n^{veh}}{t_1 + t_2} \)

• \( t_2 = \frac{\text{Segment Length}}{\text{Speed Limit}} \)
Sources of Flow Estimation Error

• Occlusions in counting vehicles
  – Camera occluded by large-sized vehicles (buses, trucks, etc.)
  – Objects on medians (trees, bridge columns, etc.)
  – Raindrops on camera’s lense

• Counting vehicles near segment boundaries

• $t_2$ assumption
Validation: Qualitative Results

- Estimated flows on network correspond to expectations by
  - Time-of-day
  - Direction

**Time of Day period boundaries:**
- Morning: 7:30 – 10:00 AM
- Noon: 12:00 – 2:00 PM
- Afternoon: 2:00 – 4:00PM
Validation: Quantitative Results

- Comparing video-based flow estimates to road tube counts
- Summary Statistics on Differences and Rel. Differences between the two
- Considering 3 time-of-day periods x 10 segment-directions

<table>
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<tr>
<th>Differences [veh/hr] [1]</th>
<th></th>
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<tbody>
<tr>
<td>Average of Differences</td>
<td>23.34</td>
</tr>
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<td>Average of Abs. Difference</td>
<td>56.36</td>
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<tr>
<td>Std. Deviation of Differences</td>
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<td>Std. Deviation of Abs. Differences</td>
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</tr>
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<tbody>
<tr>
<td>Average of Rel. Difference</td>
<td>0.10</td>
</tr>
<tr>
<td>Average of Absolute Rel. Difference</td>
<td>0.22</td>
</tr>
<tr>
<td>Std. Deviation of Rel. Difference</td>
<td>0.25</td>
</tr>
<tr>
<td>Std. Deviation of Absolute Rel. Difference</td>
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Validation: Quantitative Results

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Validation: Quantitative Results, cont.

• Analyzing the accuracy of video-based flow estimates

• Abs. $RD = \left| \frac{Video\ Avg.\ Flow - Tube\ Avg.\ Flow}{Tube\ Avg.\ Flow} \right|$

  $= \beta_0 + \beta_1 \log(CV) + \beta_2 No.\ of\ Passes$

Linear regression results

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.481719</td>
<td>0.070913</td>
<td>6.793</td>
<td>2.7E-07</td>
</tr>
<tr>
<td>Log(CV)</td>
<td>0.151637</td>
<td>0.65554</td>
<td>2.313</td>
<td>0.0286</td>
</tr>
<tr>
<td>Number of Passes</td>
<td>-0.013223</td>
<td>0.004896</td>
<td>-2.652</td>
<td>0.0132</td>
</tr>
</tbody>
</table>

$N = 30$, $R^2 = 0.321$
Validation: Quantitative Results, cont.

• Analyzing the variability of video-based flow estimates

• \( \log(CV) = \beta_0 + \beta_1 \text{Avg. Flow} + \beta_2 \text{Avg. Obs. Duration} \)
  
  \(+ \beta_3 I(\text{Noon}) + \beta_4 I(\text{Afternoon}) \)

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<tr>
<td>(Intercept)</td>
<td>0.1098115</td>
<td>0.0883032</td>
<td>1.244</td>
<td>0.2161</td>
</tr>
<tr>
<td>Avg. Flow (veh/hr)</td>
<td>-0.0011544</td>
<td>0.0001525</td>
<td>-7.572</td>
<td>8.09E-12</td>
</tr>
<tr>
<td>Avg. Obs. Duration (min)</td>
<td>-0.0042786</td>
<td>0.0005254</td>
<td>-8.143</td>
<td>3.96E-13</td>
</tr>
<tr>
<td>Noon</td>
<td>-0.1323062</td>
<td>0.0740469</td>
<td>-1.787</td>
<td>0.0765</td>
</tr>
<tr>
<td>Afternoon</td>
<td>-0.0787282</td>
<td>0.0737663</td>
<td>-1.067</td>
<td>0.2880</td>
</tr>
</tbody>
</table>

N =30, \( R^2 = 0.458 \)
Validation: Aggregating Flow Estimates into VMT Results

• Vehicle-miles-traveled (VMT) estimates across 10 segment-directions

• Road tube counts-based VMT estimate = 9,125 veh-miles/12 hours

• Video-based VMT estimate = 9,765 veh-miles/12 hours

• Recognizing that video-based flow estimates and road tube-based counts are subject to measurement errors, the two VMT results are strikingly similar
Conclusion

• Flow estimates
  – Reasonable and consistent with expectation reflecting local knowledge
  – Video-based estimates are fairly close to “ground truth” counts

• Accuracy and variability of flow estimates
  – Coefficients of explanatory variables are mostly statistically significant
  – Signs of coefficients of explanatory variables consistent with prior expectations

• VMT estimates
  – Similar when using video-based flow estimates and tube counts
  – No data collection effort needed for video-based estimates
Future Research

• Improve traffic flow estimates
  – Develop refinements to video-based estimates
  – Further validate estimates

• Develop automatic extraction of vehicle location and time-stamp data from video imagery for operational applications

• Extend validation and demonstration to larger urban transit agencies

• Determine number of bus passes needed to achieve reliable flow estimates for different types of segments
• Contact information
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  – Mark McCord: mccord.2@osu.edu
  – Benjamin Coifman: coifman.1@osu.edu
  – Giovani Hansel: hansel.21@osu.edu

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