Distributed Travel Mode Estimation

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Abstract
The Danish Road Directorate (DRD) is gathering near-realtime floating vehicle data from commercial fleet operator units to gather historic traffic patterns and to determine the real-time state of the infrastructure. So far data has only been retrieved from regular GPS units in motorised vehicles. DRD is now introducing smartphone apps to get better coverage of the road infrastructure. With this the need to estimate the travel mode of each smartphone becomes clear. This paper suggests a simple method for processing data from sensors available on most smartphones today to detect the travel mode while reporting GPS coordinates.

KEYWORDS: floating vehicle data, travel mode, smartphone, distributed processing

Introduction
About a decade ago only the most advanced in-vehicle units were capable of storing positional data and even fewer were able to transmit this in real-time to central servers. Today the number of units capable of doing this has increased to represent a significant penetration even to the regular consumer market.

For half a decade DRD has been collecting floating vehicle data from commercial fleet operators. These data originate from cars, lorries, or trucks. To increase the number of units supplying information, DRD have had smartphone apps developed which continuously will report the position of a smartphone when in use. In this case the unit is no longer bound to the above mentioned travel modes. One problem with data from smartphone apps is that if coordinates cannot be trusted to originate from a motorised vehicle, the data are irrelevant to most driver information systems. A solution to this is to let the smartphone detect the mode of transportation automatically, and report this as part of the information relayed to the DRD.

The aim of the work described here is to develop a service for smartphones to estimate their transportation mode. The estimation process should be carried out on the smartphone using sensors readily available within the smartphone itself. This in itself is not a new subject, but the focus of this work is to make the estimation as simple as possible. To make the workload on the smartphone as little as possible, it has been prioritised to find procedures with little computational complexity. As the use of some sensors tends to drain the smartphone battery very quickly the use of these to estimate the travel mode has also been limited.

The need for travel mode estimation
The importance of finding the correct travel mode can be highlighted with a few examples: When a GPS unit in a car driving on an urban road reports a decrease in speed it is fair to assume that the overall speed of that road is decreasing. If the decrease is reported from
several units the probability of the overall speed actually decreasing will be even higher. Now assume that 20 units simultaneously report the same decrease in speed at the same road. This may result in other drivers being asked to avoid the specific road to lower the risk of queuing. Assume that the GPS units reporting the decrease are in fact smartphones, and that 20 of these belong to people travelling on the same bus. Now having the bus pull over for a stop will have dramatic effects on the average speed reported on that road. Similarly interpreting cyclist information as actual motorized vehicular traffic movements may result in reporting too high speeds on central city roads during rush hour, as well as too low speeds during regular traffic.

Travel mode estimation is also a fundamental task for urban transportation planning, modelling, and management. Travel modes have traditionally been estimated based on household travel surveys conducted through self-administrated (either mailed or Internet-based) and/or personal interview approaches. Within recent years the use of surveying individual travel behaviour based on positional data has gained increasing attention in transport research due to the more accurate and reliable information, and the minimized burden on the participants. Most methods today rely on post-collection calculation on centralized servers using only GPS information. However, within recent years the potential of using smartphones for spatial data collection for different transport related purposes has increased due to the development of smartphone technology and application possibilities. The advance in functionality and capability enables an increasing use for personal monitoring where applications take advantage of the location and movement detecting capabilities e.g. GPS, GMS, and accelerometers.

The use of smartphones for tracking of movements in cities offers a lot of opportunities for different domains within ITS (e.g. spatial planning, mobility studies, traffic surveillance, personalized services, etc.). Hence both the private and public sector have acknowledged the need for a monitoring instrument of both motorized and non-motorized movements demonstrating how route choices in urban environments are made.

**Estimation based on position data**

If travel mode estimation is essential and the smartphone is not capable of estimating it itself, the travel mode estimation has to be done at the part receiving data from the smartphone. The presently developed DRD smartphone app reports point information every 10-15 seconds. Using sequences of these data it is possible to estimate a number of measures. These measures include, but are not limited to:

- **Infrastructural correlation vector, ICV.** A multi-component vector, where each coordinate corresponds to an infrastructure type like railway, roads, ferry routes, footpaths, or airplane corridors.

- **Registered traversal vector, RTV.** A 2D vector with average course and speed based on information reported from the unit.

- **Euclidean travel vector, ETV.** A 2D vector as above, but the course and speed are recalculated from positional information.

- **General direction of movement, GDM.** The direction from a previous point (less than a minute old) to the latest point.
These measures can be used for coarse travel mode estimation. The GDM can be used to estimate the ICV. If the ICV indicates low correlation to roads and railways, but high ferry route correlation, the travel is most likely by ferry.

RTV or ETV with speeds

- above 60 km/h indicates motorised transportation mode like truck, lorry, car, or train.
- exceeding 300 km/h would indicate helicopters or airplanes.
- more than 800 km/h are probably caused by airplanes.
- less than 6 km/h over prolonged time can indicate either pedestrian or congested traffic of any kind.
- that are fairly constant around 15 to 25 km/h with complete stops may come from cyclists or busses.

Even though this information can distinguish how some of the sequences are generated, many sequences will only be estimated with very low certainty. To increase the precision of the resulting information these sequences could be dropped if the target is vehicle information systems. This will result in discarding much information which may be relevant, and it may even prove counter effective, as rush hour reduced speeds can reduce the estimation quality.

Increasing the number of possible travel modes to check for severely complicates the travel mode estimation. If only positional information is available, probably even at a low frequency, the task may be unsolvable.

**Distributed estimation**

To develop a method for easy travel mode estimation an Android app has been developed. When in use this app will report positions and accelerometer measurements to a central server. Also the current transportation mode (walk/run, bike, car, bus, train, and other) is reported as selected by the user of the app. How the smartphone is carried will also influence the measurements made by the accelerometers. If the smartphone is mounted in a fixed position e.g. in the front windscreen of a car, it is more likely to measure changes in acceleration of the car than if it was loosely placed e.g. in the pocket of the driver. For this reason the user is requested to select a carrying/mounting method for each trip. For simplicity it is assumed that each trip has a single travel mode associated with it.

The accelerometer measurements are made using a three-axis accelerometer build into the smartphone. This accelerometer measures the acceleration in three perpendicular directions. Since no guarantee can be made as to how the smartphone is oriented during transport, or even that the orientation of the smartphone is fixed during a single trip, only the size of the resulting acceleration is used.

Figure 1 shows two histograms for accelerometer data from a bike trip and a car trip. A visual difference between these two can be easily spotted, as the values for the bike trip tend to spread out over a larger spectrum than the car trip values.
Figure 1: Distributions of accelerometer measurements for (a) a bike trip, and (b) a car trip.

Table 1 shows a number of statistical measures for accelerometer data from a small number of trips. Of these only the standard deviation seems to differ between the different travel modes, and it is evident that the standard deviation from car travel is significantly lower than that of any of the other travel modes.

<table>
<thead>
<tr>
<th>Travel mode</th>
<th>Min value</th>
<th>Max value</th>
<th>Average</th>
<th>Std. deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walk</td>
<td>1.21</td>
<td>25.46</td>
<td>11.68</td>
<td>5.44</td>
</tr>
<tr>
<td>Walk</td>
<td>3.46</td>
<td>18.12</td>
<td>9.83</td>
<td>1.46</td>
</tr>
<tr>
<td>Bike</td>
<td>6.78</td>
<td>14.67</td>
<td>10.34</td>
<td>1.04</td>
</tr>
<tr>
<td>Bike</td>
<td>3.70</td>
<td>20.05</td>
<td>10.16</td>
<td>2.34</td>
</tr>
<tr>
<td>Bike</td>
<td>2.51</td>
<td>19.68</td>
<td>9.94</td>
<td>2.08</td>
</tr>
<tr>
<td>Car</td>
<td>8.14</td>
<td>11.25</td>
<td>9.39</td>
<td>0.37</td>
</tr>
<tr>
<td>Car</td>
<td>8.41</td>
<td>11.46</td>
<td>9.45</td>
<td>0.27</td>
</tr>
<tr>
<td>Train</td>
<td>3.23</td>
<td>19.72</td>
<td>9.61</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Table 1: Statistical measures for select trips.

Based on the observations described here a small estimation scheme, illustrated in Figure 2, is constructed. To find the standard deviation of the accelerometer measurements no other sensor than the accelerometer has to be turned on. The standard deviation is continuously calculated over the last few minutes. As long as this value over a period of time does not change significantly there will be no need to use other on-board sensors. If the standard deviation should rise, the GPS will have to be turned on so the speed can be calculated. This
is done by using a number of consecutively measured positions. If distinguishing between travelling by train and e.g. running is necessary, a correlation between the path travelled (as measured using the GPS) and the surrounding train tracks should be calculated. Calculating this requires a digital representation of the train tracks, which most often will be significantly less than a full representation of the road infrastructure. Therefore it will be possible to have this representation on most smartphones.

**Figure 2: Simple determination graph for estimating travel mode.**

**Further work**

The travel mode estimations presented here has been done on a small collection of trips only, and therefore it cannot be guaranteed that the results will be applicable to all smartphones and/or trips. Further work and a larger amount of recorded trips are necessary to validate the method before applying it to real life traffic data.

The method described here gives a categorical answer to the question of current travel mode. This is useful to determine if reported data should be used or not. If instead the method provided an array of probabilities for a number of travel modes the receiver could choose to use data with a lower probability of coming from car travel if the amount of other data available was too little. To obtain this the statistical measures of accelerometer data as well as speed and correlation to road and railway structures could be incorporated in e.g. a Bayesian network.

**Conclusion**

This work has shown that it is possible to construct a simple method to determine the travel mode of a smartphone. The method described uses accelerometer data only, as long as these
will provide enough evidence of the travel mode. This method ensures that the computational complexity of the travel mode estimation is kept to a minimum.

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