FCD in the real world – system capabilities and applications

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Abstract
The use of Floating Car Data (FCD) systems for the generation of traffic information has been discussed in numerous publications, many of which are based on simulated data or on a small number of vehicles collecting data over a limited time span. We present FLEET, a real-world FCD system, which has been continuously operating since 2003, collecting data from thousands of taxis in the Vienna region. We describe the system capabilities, our operating experience, and selected applications accumulated over the past years.

Keywords:
Floating car data, probe vehicles

Introduction

Information about the traffic state is of great importance for a variety of tasks. These tasks are usually performed and managed by public authorities or private enterprises to the benefit of the general public. Floating Car Data (FCD) systems, wherein a number of vehicles within the traffic stream act as probes, are an inexpensive source of traffic information.

The AIT Mobility Department has developed FLEET, a system optimized for managing and processing FCD, which has been operating in Vienna since 2003 [1]. FLEET reuses data from existing fleet management systems, thus keeping investment costs for infrastructure and hardware low. The system architecture is scalable and different FCD sources can be easily integrated. FLEET’s layer architecture is shown in Figure 1: Vehicle fleets collect raw data (1), which is processed and aggregated (2). Based on this data, advanced applications generate specific information, such as real-time congestion alerts (3). FLEET has been successfully deployed and operated in various real-world scenarios including Vienna, Lyon and Düsseldorf [2].

Different types of vehicle fleets such as taxis, delivery service vehicles, or public transport, which rely on satellite-based positioning (GPS), can be used as probe vehicles for FLEET.
The data quality achievable from a vehicle fleet depends on fleet specific parameters such as total fleet mileage, sample size with regard to overall traffic, and the possibility to obtain data in real-time. Most recent operating FCD systems are based on taxi fleets, for instance the systems in Berlin (4,000 taxis) [3] or Beijing (10,000 taxis) [4].

The FLEET system in Vienna currently collects data from approximately 3,000 taxis with an annual mileage of over 90 million kilometers for the traffic center of ITS Vienna region. The system estimates the average speed per road element and time interval to determine a traffic state and to compute short and medium-term predictions. FLEET provides tools to compute prototypical time series with statistical learning methods. This enables to provide services such as automated traffic congestion warning and dynamic real-time routing. [5] The results obtained from FCD were evaluated and validated extensively using ground truth data from systems such as automatic number plate recognition (ANPR). Figure 2 shows an evaluation example, where travel times along an urban corridor in Vienna were recorded using ANPR and compared to travel times from the FLEET system, stationary radar and infrared sensors (not shown). The study showed that FLEET detects travel time peaks in case of congestions more robustly than stationary sensor infrastructure, although very high peaks

Figure 1 – FLEET layers

FLEET Vienna

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are not recognized to the full extent. The mean relative travel time difference is 2.5 %, with a standard deviation of 15 %. Accuracy of travel time prediction increases with higher sample size [7]. In the following sections we describe some other FCD applications.

![Comparing FCD and ANPR Timeseries](image)

**Figure 2 – FCD travel times vs. ground truth (ANPR) [7]**

**Quality control for static sensor infrastructure**

Many current ITS applications rely heavily on traffic data from loop detectors. Identifying faulty traffic detectors thus is a vital part of ITS quality assurance. Certain types of sensor failures, such as sensor outage or reporting a constant measurement value over a long time period, are trivial to detect. Other types of loop detector faults are often subtle and hard to distinguish from real, but unusual traffic conditions. FCD has been successfully employed as an independent information source for the quality control of loop detectors [8].

This fault detection is based on the residuals of a nonlinear regression model fitted to the relation between detector readings and FCD traffic speeds. In order to identify detector errors, the model residuals are inspected and compared to an expected residual distribution obtained from trusted training data. The thresholds involved in the fault detection process are derived from demanded false-alarm rates.
Figure 3 – Sensor traffic flow plotted against FCD speed

Figure 3 shows interval-aggregated traffic flow measurements obtained by a loop detector on a main artery road in Vienna plotted against travel speed of probe vehicles passing the detector. The color in Figure 3 encodes the prediction error of the model (green = low, red=high), where the threshold between a ‘low’ and ‘high’ error is the standard deviation of the residuals from the principal curve (dashed line in Fig. 3) to the data. The residuals are normally distribution, such that two thirds of the training data have ‘low’ residuals.

Assessment of traffic message system quality

Figure 4 visualizes the estimated traffic state on an urban corridor in the center of Vienna as a matrix of corridor segments (rows) and 15-minutes intervals (columns). The cell color encodes traffic density, where traffic congestions are depicted in red. The respective number of measurements is encoded within the opacity level: Values based on sets of measurements smaller than a given threshold are displayed with increasing transparency, which results in white cells for times and spaces with no measurements. This method permits the localization of events, both in space and time, e.g. congestion between Brigittenauer Lände and Nußdorfer Straße from 07:00 until 09:45. One use case is the assessment of traffic message system quality [6]: Event information extracted from FCD sources can be compared with spatial and temporal extent of relevant traffic messages.
**Evaluation of traffic-influencing measures**

Traffic state information generated by FLEET has been successfully used in traffic state analyses to evaluate the effectiveness of traffic control measures such as traffic signaling optimization. Figure 5 compares average floating car speeds before (black) and after (orange) the traffic signaling optimization in question. The comparison shows that the traffic influencing measure could increase average travel speed on the evaluated route, especially during rush hours. Care was taken to ensure that only data from days with comparable traffic volume were considered in the comparison.

This analysis could be reproduced for all driving directions within the investigated area. The statistical significance of the optimization impact on traffic performance during selected times of the day was shown. Using FCD, it was possible to analyze the change of traffic performance without any additional infrastructure or installation costs.
Another approach uses FCD position data to determine hot spots with stop-and-go traffic and estimates traffic queue lengths. A common advantage of using this kind of data for analyses is that data collection does not have to be planned beforehand since FCD are recorded continuously. This makes FCD-based analyses very flexible, especially in an environment where it would be difficult (for economic or organizational reasons) to install dedicated temporary sensor infrastructure such as ANPR systems.

**Conclusions and Further Research**

FCD systems are a low-cost source of reliable traffic information. By reusing data collected from existing vehicle fleets, systems like FLEET can be deployed with minimum effort and provide valuable input for numerous applications in real-time. Current and further research topics include reliability management, evaluation of traffic quality, alternative prognosis methods, and incident detection based on FCD.

**Acknowledgements**

This work has been funded by the Austrian Research promotion Agency (FFG) under grants no. 831730 (REFEREE) and 835781 (QS4TMC).
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