# Demo: Road Speed Profile: From GPS Traces to Real-time Traffic Speed

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## ABSTRACT

GPS-Enabled devices such as smartphones are widely used. With GPS chips that uses lower energy, GPS location and traces are widely collected by different users. One important useful usage is extracting the speed of a user in vehicle to determine real-time and historical speed of traffic in each road in the city. Accumulating these speed records allows the creation of speed profiles. Speed profiles define the general behavior (i.e., traffic speed) of each road at each time of the day. In this demo, we show an energy-efficient location acquisition algorithm to collect traces, a map-matching algorithm to construct the path that the user has taken, an algorithm to calculate the average speed of the vehicle and a speed profile of different road segments used to provide historical, real-time and predicted traffic speed. We also display the whole system in action with data of over 1000 traces collected in Trento, Italy.

## **Keywords**

Intelligent Transportation Systems, Floating Car Data

## 1. INTRODUCTION

As modern hand-held location-aware devices such as smartphones are rapidly used, user localization is becoming an essential information to be exploited by a variety of services. As the energy consumption of GPS chips integrated in smartphones are rapidly decreasing, users are incrementally using such location-based and location-aware services [1]. Such usage creates a huge amount of spatio-temporal data that could entail a lot of information about mobility patterns, traffic status and driving behavior in urban and suburban areas. With this knowledge, there is a great potential in creating systems that utilize such data to detect, predict and monitor traffic conditions. Being motivated by the availability of such data, a lot of research is carried out to create traffic monitoring systems that could be based on such entailed information without the deployment of expensive traffic management infrastructure to acquire mostly the same data. [2]

Spatio-temporal data are typically a trace of GPS points. Each point consists of a latitude, longitude and timestamp. Such traces

*MobiHoc'14*, August 11–14, 2014, Philadelphia, PA, USA. ACM 978-1-4503-2620-9/14/08. http://dx.doi.org/10.1145/2632951.2636055. could be easily collected using smartphones or even vehicles with GPS-enabled devices. These points are then mapped to a digital map, then matched with nearby roads, then a smart shortest path is calculated between each two points to reconstruct the full path that the user has taken. This process is defined as map-matching. [2]

With the reconstructed path and timestamps, the speed of the vehicle could be easily inferred in each road segment. The road segment is defined as small road between two subsequent intersections in any street. The speed of traffic flow in this road segment could be provided immediately as a real-time speed update for any digital journey planner such as Google Maps or SUPERHUB [3] to define an optimal fastest route between two points in a map. Then, speed records for each road segment are accumulated and stored to create the speed profile. It is defined as series of speed records with timestamps throughout different periods of the day (e.g. 10AM, morning, afternoon, ..) and different days such as weekends, working days or specific day of the week annotated with weather status and existence of any big events around. Such data defines the general behavior of the road in every hour in each day. However, this data alone is incapable of predicting disruptive events that might happen in the future. However, real-time updates inferred from GPS traces collected in real-time can easily infer such unexpected events.

Therefore, the speed profile is capable of delivering 1) real-time speed updates as long as there are new traces being uploaded the system, 2) estimated current and future speed based on the general behavior of the road at the specified time, and 3) all historical data collected before. Such data is a great asset to build efficient journey and route planning algorithms. Also, it would help decision makers to identify the general behavior of roads, understand where and when congestions generally occur and therefore take an action.

# 2. DATA COLLECTION

The algorithm illustrated in Alg. 1 implemented in [2] introduces an energy-efficient data localization algorithm to lower the sampling rate of the algorithm for the aim of preserving the energy of smartphones while maintaining the performance of map-matching algorithm. Of course, the lower the GPS samples, the lower the energy consumption. However, very low sampling rate could ruin the performance of the map-matching algorithm as seen in fig. **??**. Using this algorithm, we balance between both the constraints of energy preservation and map-matching performance. [2]

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Figure 1: High sampling pling Figure 3: Low sampling Figure 4: Reconstructed paths in the case of a low, medium and high GPS sampling rate. The dotted line is the original path, the continuous line is reconstructed path.

#### Algorithm 1 Location sampling algorithm

- 1: accTHR = 30;  $\triangleright$  Localization accuracy threshold.
- 2: location = networkLocalization();
- 3: if location.accuracy  $\geq$  accTHR then
- 4: location = GPSLocalization();
- 5: **end if**

## 3. DATA ANALYSIS

#### 3.1 Data Preprocessing

Once data is collected, it's transferred to the server to be analyzed. After passing an initial preprocessing check, it's passed to two subsequent phases, the map-matching step then the speed calculation step. Data preprocessing checks if the duration of the journey is valid and the time difference between each two subsequent points doesn't exceed 5 minutes, the GPS trace is valid. If the trace has any difference more than 5 minutes, it's split into two traces.

## **3.2 Map Matching**

Map-matching is the process of positioning each location point into a digital map, reference it to the most relevant adjacent road link, reconstruct the path between each road link to fully reconstruct the whole journey followed by the vehicle or the car. In this demo, we use the ST-Matching algorithm [4] as it's widely accepted algorithm for reconstructing paths using low sampling GPS traces.

The first step of ST-Matching algorithm is projecting the GPS point on the nearest road link. Projection here means finding the nearest road link to the GPS point. When sampling rate is very frequent, this could be enough to reconstruct the full path preciously. However, with low sampling rate, ST-Matching algorithm takes an additional step to find the path between two subsequent road links. Shortest path calculated by Dijkstra algorithm could be based on shortest time or shortest length [4]. In our implementation, we use the shortest length as it was proved to be more precise. Finally, the full path followed by the user is fully reconstructed usually by an average performance of 85% as indicated in [2] when the sampling rate is around 30-40 seconds.

## 3.3 Speed Calculation

Using Open Street Maps as our digital map, we calculate the speed between two subsequent GPS points based on the distance between them divided by the time difference. Calculating the distance has to be precise and well-defined to avoid any noise. Therefore, we calculate the distance by determining the distance between the projected GPS point on the nearest road link. The projected GPS point is the new GPS point inside the nearest road link which is determined by taking a vertical line starting from the original GPS point coordinates to the closest point in the road segment. Distance between these two projected GPS coordinates are calculated and divided by the time difference between their corresponding timestamps.

## 3.4 Speed Profiles

Speed profile as we define here is basically set of statistical tools that identifies the general average speed in each half an hour of the day. As generally known, average speed of traffic follows a pattern based on hour of the day and day of the week. Based on this common sense and when there is not real-time updates, we estimate the current average speed of the road in a specific time by looking up historical data of the same time in the same day. If number of speed samples is insufficient, we generalize the look up to include similar days (working days, or weekend) or to look up adjacent roads. Finally, if no data exists, we return the maximum speed multiplied by the average speed deduction percentage on the same road type (i.e., roadway, motorway, etc) at the same time of the day around the road.

## 4. CONCLUSIONS

GPS traces of smartphones that users collect while driving are a great source to infer average speed of road traffic. Such data is collected from many users continuously then analyzed to provide real-time updates of traffic speed in a city. With the accumulation of this data, a speed profile is created. Speed profiles define the speed of car traffic in each road at a certain time of the day. We introduce an algorithm that efficiently collects the GPS traces and another algorithm to process the traces and extracts the average speed of traffic flow in each road.

### 5. ACKNOWLEDGMENT

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## 6. **REFERENCES**

- [1] Foursquare. https://foursquare.com/.
- [2] M. Alrefaie, I. Carreras, F. Cartolano, R. Di Cello, and F. De Rango. Map matching accuracy: Energy efficient location sampling using smartphones. In *Intelligent Transportation Systems - (ITSC), 2013 16th International IEEE Conference on*, pages 2243–2248, Oct 2013.
- [3] P. J. Forbes, S. Wells, J. Masthoff, and H. Nguyen. Superhub: Integrating behaviour change theories into a sustainable urban-mobility platform. In Using Technology to Facilitate Behaviour Change and Support Healthy, Sustainable Living Workshop at BHCI, 2012.
- [4] Y. Zheng, Q. Li, Y. Chen, X. Xie, and W.-Y. Ma. Understanding mobility based on gps data. In *Proc. of UBICOMP*, Seoul, Korea, 2008.