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On-Street Parking Search Time Estimation Using FCD Data

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Abstract

This paper focuses on modelling on-street parking search time by using FCD data coming from probe vehicles. It is based on data detected by probe vehicles, which allow to identify the typical spiral around the destination that vehicles perform in the final part of the trip to find a parking place. The proposed model is suitable to be used either in real-time to support user information and dynamic routing, or off-line for a better assessment of transport plans.

A real-size application to the city of Rome is presented to show the promising results obtained for the estimation of parking search time in urban areas.

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Keywords: FCD data; on-street parking; car travel time; parking search time; modeling

1. Introduction

In urban areas parking search is a considerable problem, which affects car travel time, especially in city centres where on-street parking lots are usually few compared with demand. Literature in this field mostly investigates this problem from a strategic point of view when studying the impacts assessment of parking policies neglecting the problem of reproduction user behaviour in park search and the relative time spent to find a parking place at destination, which can deeply affect car travel time modelling and estimation. Nowadays, this failure plays a key role for user information, both real-time and off-line, because the underestimation of car travel times leads to overestimate car mode attractiveness with respect to others. Moreover, ignoring parking search time implies considerable

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approximations in assessing transfer times and waiting for public transport in multimodal journeys, especially in case of low-frequency services.

The parking problem involves different issues, such as parking policies, parking search behavior, parking search time estimation. It has been investigated using different approaches, such as stated preference surveys, field observations, discrete choice models, numerical and simulation models. In recent years, the introduction of a huge amount of GPS data leads the research to new data driven models. In this field, Kaplan and Bekhor (2011), Montini *et al.* (2012) and Van Der Waerden *et al.* (2014), can be cited.

Focusing on street parking, which is the aim of this paper, a recent review can be found in Brooke *et al.* (2014) that classifies the research according to the methodological approach pointing out advantages and disadvantages, as well as applicability.

Our study starts from the consideration that in urban areas usually no data about parking (i.e. interviews) as well as no information about final destination of trips are available, but a huge amount of Floating Car Data (FCD) are offered by new technologies at a very low cost. The literature presents very few papers that investigate the problem of estimating on-street parking time (e.g. Belloche,2015) but none seems to consider the opportunity offered by FCD data. For this reason, this paper proposes a modelling framework able to estimate the time spent in parking search at the roadside by using FCD data, only.

Section 2 describes the proposed methodology, while section 3 briefly reports the promising results of a real-size application to the city of Rome. Finally, section 4 summarizes the conclusions of this research and gives some considerations for further developments.

2. Methodology

This study focuses on modelling time spent in on-street parking search by analysing paths that vehicles perform in the final part of their trips before reaching the destination, through the use of FCD data.

The model has been calibrated as a function of FCD data time sampling; it allows to identify the ceiling of the parking search beginning, from which users' behaviour in park search can be assumed to be a spiral trajectory around destination as pictured in Fig. 1.

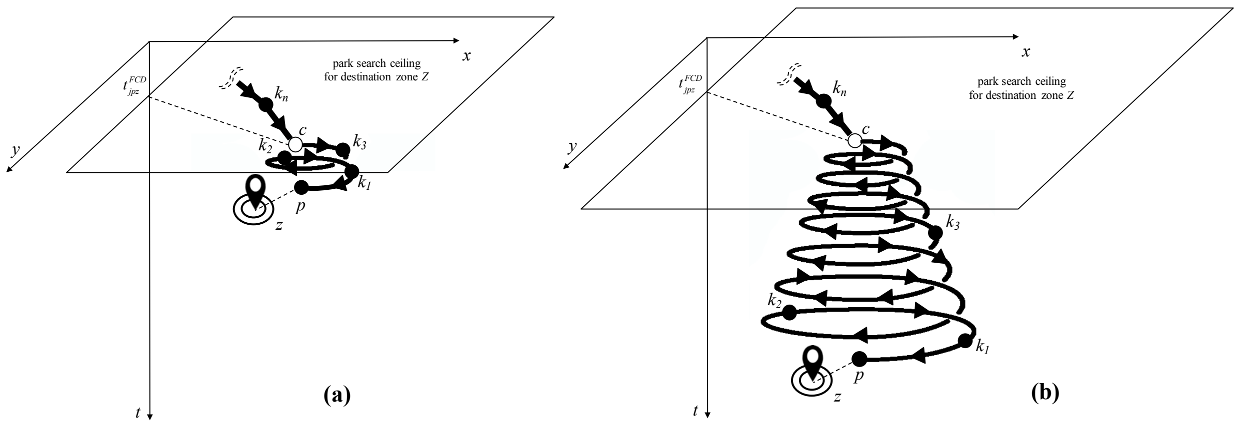


Fig. 1. (a) Example of on-street parking trajectory in case of undersaturation; (b) case of oversaturation

Fig. 1 represents the trajectory of a generic vehicle parking in p near its destination z within a traffic zone Z. The amplitude of the spiral is related to the difficulty of parking at the roadside nearby destination z: Fig. 1(a) describes the case of a wide availability of parking lots at the roadside (i.e. under-capacity), while Fig. 1(b) describes the case of limited availability for the same destination (i.e. near-capacity).

In parking search, in fact, the driver begins to turn around its destination gradually expanding the circle of his/her research starting from a ceiling point c, and the phase of on-street parking search can be captured by analysing FCD data made of vehicle detected points k_i.

Hence, the problem of estimating on-street parking time can be solved by identifying, at first, the likely begin of parking search (i.e. when user starts traveling spiral paths) and, then, by computing the parking search time.

This study proposes to model vehicle trajectories during park search as:

$$\rho_s = \beta\theta_s \tag{1}$$

$$x = \beta\theta_s \cos(\theta_s) \tag{2}$$

$$y = \beta\theta_s \sin(\theta_s) \tag{3}$$

$$t=\upsilon\theta_s \tag{4}$$

which represent the spiral equations in polar coordinates (ρ_s , θ_s), with a spiral pitch of $2\pi\beta$ and a spiral development equal to the average of circumferences having radius of $(n\text{-}1)2\pi\beta$ and $n2\pi\beta$. υ is the parameter that represents speed of uniform motion in time axis t.

In the same way, vehicle trajectories approaching the parking search phase are assumed linear as follows:

$$x = \rho_l \cos(\theta_l) \tag{5}$$

$$y = \rho_l \sin(\theta_l) \tag{6}$$

$$t=\upsilon\theta_l \tag{7}$$

where ρ_l represents the line length, θ_l is the line angular coordinate, and υ is the parameter that represents speed of uniform motion in time axis t.

The methodology proposed to estimate the on-street park time for a given destination zone Z within the study area is based on the road network of the study area represented through a supply model (section 2.1), which is used within a map matching procedure (section 2.3) to associate available FCD data (section 2.2) to the transport network. The matching procedure allows to define the set of probe vehicles per destination zone used to obtain revealed travel times in the considered time period τ that are compared with predicted ones, which are carried out by using a dynamic shortest path algorithm (section 2.4).

Revealed and predicted travel times are used to estimate a gap function (section 2.5) that allows us to define the park search ceiling distance per destination traffic zone Z, through which the on-street parking time per destination zone Z and time period τ is estimated (section 2.6).

In the following, each component of this methodology, as well as the solution algorithm, is described in detail.

2.1. Supply Model

According to principles of transport system modelling, the road network and its performances (i.e. travel times and costs) are represented by a supply network model. Such a model is made of a graph, which represents the transport network in terms of streets and intersections, and cost functions, which allow to calculate time and cost for each link of the transport network (i.e. Level of Service - LoS - attributes) in relation to the time period τ of the day (e.g. 15 minutes). If the proposed methodology is used for real-time purposes (see introduction), the supply model is updated in its performances (i.e. link times and costs) at fixed time steps according to available real-time data sources (e.g. traffic sensors, FCD data, crowdsourcing, and so on). The supply model, and in particular its graph, is formed for the most efficient and least time-consuming use of the dynamic shortest path model (see section 2.4). Further details about the representation of transport network through supply models can be found in Cascetta (2009).

2.2. Floating Car data

FCD data are made of information about position and speed of a probe vehicle. Data are characterized by a sampling frequency defined both in time and space. The space sampling is carried out mainly for data recovery in case of covering failure. The track record of the data consists of the following fields: Vehicle ID, Day, Time, Latitude, Longitude, Speed, Direction, Quality of signal, State of motion, Distance from previous data. Although it is theoretically possible to associate further vehicle information through Vehicle ID, due to privacy, this further information is not available and for this reason it is not possible to classify FCD data for vehicle type.

Data are filtered on the basis of speed, coordinates and sequence of detected points, applying procedures able to capture and analyze outliers data and mis-identified trajectories.

2.3. Map matching procedure

FCD data geocoding allows to match each FCD sample to a link of the road network. This result is carried out by proposing a map matching algorithm (Quddus *et al.*, 2007) that compare the probability associated to each link of being candidate for a matching with a given FCD sample (i.e. vehicle point). The link with higher probability is chosen for the association. The probability of matching an FCD sample k to a link (i,j) can be calculated as:

$$P_k(i,j) = \Psi(d, \alpha, v, \gamma) \tag{8}$$

where: d is the distance of k from link (i,j); α is the angular deviation between the direction of speed vector and the directionality of the link; v is the traffic flow allowed directionalities and γ is the function parameter.
Parameter γ can be calibrated taking into account the number of the possible associations without errors of FCD data for classes of values of the other considered variables, while v allows to reduce the set of candidate links according to permitted link direction. An example of link matching probability is pictured in Fig. 2.

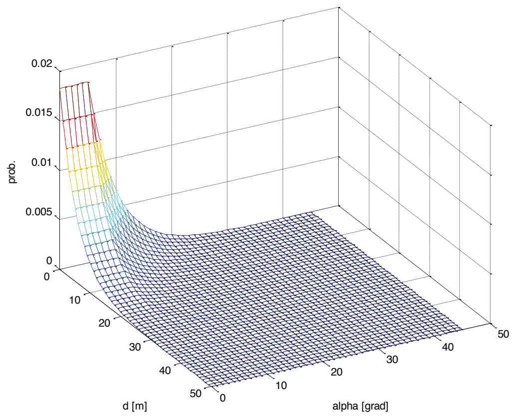


Fig. 2. Example of link matching probability computation

2.4. Dynamic shortest path computation

The estimation of predicted LoS attributes from vehicle position k to its parking position p is obtained through the search of the minimum cost paths of the road network. Such a search is carried out by using dynamic algorithms in which the minimum cost path is identified by considering the time-dependent cost of link (i, j), that is:

$$c_{ij} = c_{ij}(\tau) \tag{9}$$

where τ is variable over time within the simulation period T.

The dynamic approach is necessary when network performances (costs of link) differ considerably within the simulation period, as in the case of the performance variations between peak and off-peak hours or inside the same peak hours due to congestion.

The dynamic approach achieves accurately origin-destination routes on the network, because computed according to departure time and estimated travel time of the links on the effective time of crossing them.

The used algorithm is a version of Dijkstra's algorithm proposed by Kim et al. (2013) that uses a data structure called "double-buckets" to manage the set of temporary labeled nodes, which has been adapted to consider time-dependent link costs. In order to take into account turn prohibitions at intersections, this algorithm has been modified according to the link-based shortest path algorithm proposed by Lim and Kim (2005) for which the Bellman's principle of optimality in searching shortest path is carried out as follows:

$$LEC(o,i)+TP[link(o,i),link(i,j),\tau]+LC(i,j,\tau) \leq LEC(i,j) \qquad \forall\, o,i,j \in N \tag{10}$$

where $LC(i,j,\tau)$ is the nonnegative link cost required to travel from node i to node j at time τ and $LEC(o,i)$ be the link end cost, or minimum path cost from origin to node i through $link(o,i)$ which refer to the directed link leading from node o to node i, $TP[link(o,i),link(i,j),\tau]$ is the turn penalty which implies the additional cost at node i from $link(o,i)$ to $link(i,j)$ at time τ defined according to the turning rules at intersection, assuming o,i,j belonging to the set of nodes N of the road network.

2.5. Gap function estimation

The main problem of this proposed methodology is the identification of the likely begin of parking search, that is to identify when we can assume vehicle starts to behave in order to find a parking lot at the roadside and hence when it is possible to model vehicle behavior through eqns. (1-4). This problem can be solved by using a gap function aiming at identifying the ceiling distance pictured in Fig. 1. This function can be defined through the analysis of the slope of linear regressions computed for each destination zone, comparing the FCD travel time with the travel time on the shortest path computed for all the *n-th* detected positions (FCD samples) of all vehicles parking in z within destination zone Z, that is:

$$TTFCD_{kpz} = m_z\, TTDSP_{kpz} + b_z \tag{11}$$

where $TTFCD_{kpz}$ is the travel time detected by FCD point k for a vehicle parking in p with destination in z within traffic zone Z, and $TTDSP_{kpz}$ is the corresponding shortest path travel time computed by using the dynamic shortest path algorithm described in section 2.4.

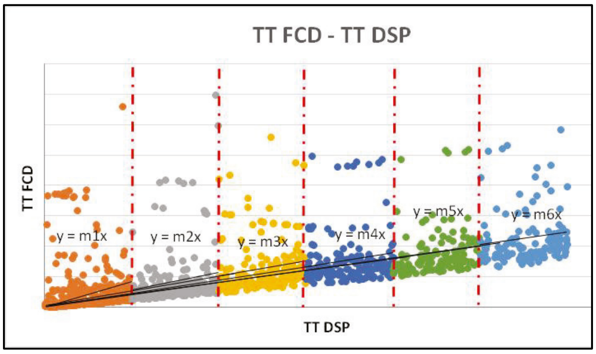
The slope of these regressions $S_P(D)$ can be represented by a differentiable function as follows:

$$S_P(D) = \Phi(D,a,c) \tag{12}$$

where D represents the distance between the detected point k and the parking point p, and a and c are parameters to be calibrated for the considered destination zone Z.

Fig. 3(a) reports an example of regressions computed for a given destination zone considering the last six points (see vertical red lines) for each detected vehicle, while Fig. 3(b) shows an example of gap function estimation.

For big road networks, an aggregation of destination zones in macro-zones is suitable to be performed. It can be done by using common clustering analysis methods applied to the slope of the above regressions.



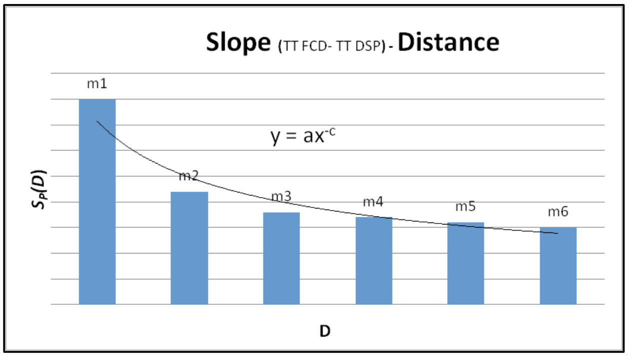


Fig. 3. (a) Comparison between FCD and DSP travel times. (b) Example of Gap function estimation for a generic traffic zone

2.6. On-street park time estimation model

In order to estimate the on-street park time for a traffic zone Z, the ceiling distance can be identified through the analysis of the derivative of function $S_P(D)$ (see section 2.5), that is:

$$\frac{\partial S_P}{\partial D} < \xi \tag{13}$$

Eqn. (13) reflects the fact that when vehicles start the parking search can be interpreted by a "sudden" change in the gap function represented by the comparison between the derivative of S_p and the threshold ξ.

Therefore, once defined the ceiling, parking search time in destination zone z, PT_z, can be calculated as the difference between FCD detected travel time and shortest path travel time within ceiling, that is the difference between the spiral length and the line length defined by eqns. (1-7) as:

$$PT = \frac{1}{2}\beta\left[\theta_s\sqrt{1+\theta_s{}^2} + ln\left(\theta_s + \sqrt{1+\theta_s{}^2}\right)\right] - \rho_l \tag{14}$$

where θ_s *is* the polar coordinate of spiral, β is the spiral parameter, so the spiral step is equal to $2\pi\beta$, and ρ_l is line polar coordinate, so the line length.

2.7. Solution algorithm

The proposed methodology can be described in terms of pseudocode for a better understanding of links between algorithm steps and equations to be implemented and applied. Such a pseudocode can be summarized as follows.

1.1 The study area is subdivided into square-shaped meshes for data map matching
1.2 *For each FCD sample k*
  1.2.1 identification of the mesh quadrant in which sample k falls
  1.2.2 definition of the set S of links (i,j) within or crossing the mesh quadrant in which sample k falls
  1.2.3 *For each link* $(i,j) \in S$
    1.2.3.1 calculation of d and α of sample k with respect to link (i,j)
    1.2.3.2 check of directionality accordance between sample k and allowed direction of traffic flow v on link (i,j)
    1.2.3.3 *if* check of directionality accordance is positive
      then
        calculate $P_k(i,j)$ through eqn (8)
      else
        set $P_k(i,j) = 0$
      end if
    End link (i,j)
  1.2.4 associate FCD sample k to the link $(i,j) \in S$ having the highest probability $P_k(i,j)>0$
End FCD k
1.3 *For each traffic zone Z*
  1.3.1 definition of the set K_Z of FCD points related to vehicles with destination in z within traffic zone Z
  1.3.2 computation of dynamic shortest path between FCD point $k \in K_Z$ and its parking position by eqn (10) on the basis of road network performances defined through link costs (9)
  1.3.3 calculation of the gap function (11) by considering the travel time detected for FCD point $k \in K_Z$ (revealed LoS attribute) and the corresponding shortest path travel time computed in step 1.3.2 (predicted LoS attribute), for all $k \in K_Z$
  1.3.4 *For each time interval* τ
    1.3.4.1 identification of the set $K_{Z\tau}$ of FCD points $k \in K_Z$, that is FCD points related to vehicles with destination in z within traffic zone Z , which are detected in time interval τ
    1.3.4.2 definition of $S_P(D)$ through eqn (12) by clustering data computed in 1.3.3 for $k \in K_{Z\tau}$
    1.3.4.3 identification of park search ceiling distance through eqn (13)
    1.3.4.4 *For each FCD sample* $k \in K_{Z\tau}$
      if position of FCD k is within ceiling distance
      then
        calculate parking time from the position of k to the vehicle parking position by using eqn (14)
      end if
    End FCD k
    1.3.4.5 Estimation of the average and the maximum (90th percentile) parking search time by considering all detected positions $k \in K_{Z\tau}$
  End time interval τ
End traffic zone Z

3. Application

The proposed methodology has been applied in the city of Rome, where a dataset of FCD data has been provided by the City Transport Agency (Roma Servizi per la Mobilità). This dataset consists of about 100.000 vehicles sampled in both time (30 s) and/or space (every 2 km) from the start of their engines to the turn off during workdays of an entire month (i.e. May). Such vehicles evolve in 9 million of vehicle movements for a total of about 78 million FCD samples, which have been subject to a validation procedure aiming at filtering outliers and mis-identifed trajectories. The validation procedure allows to identify about 4 million FCD samples, which have been rejected mainly due to loss of accuracy in data matching. For this reason, the dataset available for this study consists of about 74 million of FCD samples.

The study area is based on a zoning system made of 58 traffic zones, which are aggregated in 5 macro-zones according to the guidelines of the General Urban Traffic Plan (GUTP). GUTP 1 represents the city center, while the rest of the metropolitan area of Rome is considered through circular sectors from the center to suburbs (GUTP 5).

The methodology proposed in section 2 has been applied and an extreme summary of application results are pictured in the following figures, which report the average value of parking search time (Fig. 4) and the upper bound of the confidence interval of the average time (Fig. 5) per GUTP macro-zone within the simulation period (i.e. weekday).

Such figures clearly show the extra time needed for parking, which is about the double in the city center (GUTP 1) with respect to suburbs due to the limited on-street parking capacity in this area. Figs. 4-5 also confirms the variability of parking time within the day pointing out peaks, as expected, during rush hours.

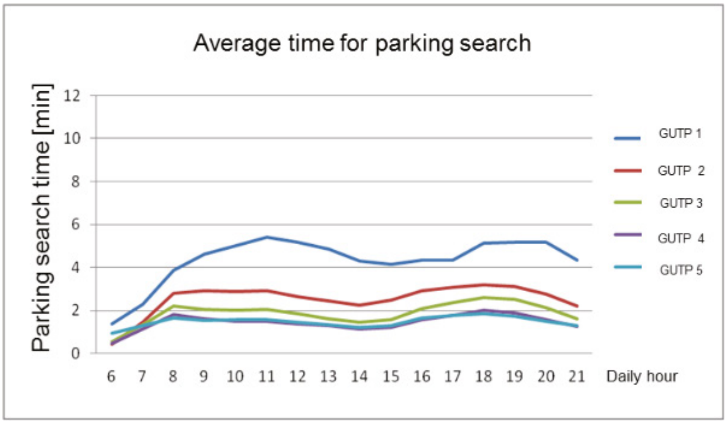


Fig. 4. Parking search time during weekdays per GUTP zone: average value

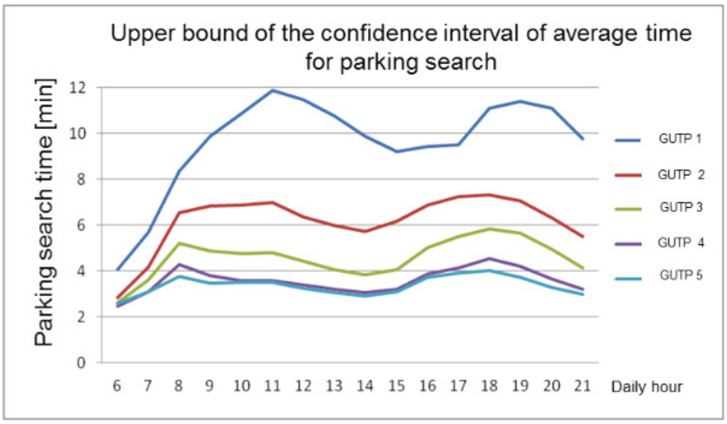


Fig. 5. Parking search time during weekdays per GUTP zone: upper bound of the confidence interval of average value

Focusing on the GUTP macro-zones during the peak hours, and deepening on the incidence of on-street parking search time with respect to the whole travel time to destination, we can see that the average on-street parking search time is about the 11% of the whole travel time for trips destined to GUTP 1 (city center), and this percentage decreases moving from the center (GUTP 1) to the suburbs (GUTP 5), where the time spent for parking search is about the 6% of the whole. In conclusion, although average travel time per GUTP is similar (about 29 minutes), the incidence of time spent in parking search in GUTP1 is quite different (+5%) with respect to GUPT5. Such an incidence varies from 7 to 8% for trips destined in the other macro-zones (GUTP 2,3,4).

4. Conclusions and further developments

In this paper authors proposed a model for on-street parking search time estimation by using FCD data coming from probe vehicles.

The modelling framework is based on the use of FCD data to detect time in which vehicles start searching a parking lot before reaching their destination. This behavior is modelled through a spiral around the destination aiming at representing the final part of the trip to find a parking place. The proposed model is suitable to be used either in off-line applications for planning or in on-line tools to assess user’s information and dynamic routing.

The application to the city of Rome allowed to show the goodness of the proposed approach and to suggest the possible future developments of this research.

Future developments mainly regard the use of more efficient algorithm of map matching, the specification and calibration of different gap functions as well as the application to more detailed zoning systems. Moreover, if actual privacy constraints on FCD data will be solved, it will be also interesting to specify and calibrate models for different vehicle types.

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