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A Fuzzy set-based method to identify the car position in a road lane at intersections by smartphone GPS data

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Abstract

Intelligent transportation systems (ITS) work by collections of data in real time. Average speed, travel time and delay at intersections are some of the most important measures, often used for monitoring the performance of transportation systems, and useful for system management and planning. In urban transportation planning, intersections are usually considered critical points, acting as bottlenecks and clog points for urban traffic. Thus, detecting the travel time at intersections in different turning directions is an activity useful to improve the urban transport efficiency. Smartphones represent a low-cost technology, with which is possible to obtain information about traffic state. However, smartphone GPS data suffer for low precision, mainly in urban areas. In this paper, we present a fuzzy set-based method for car positioning identification within road lanes near intersections using GPS data coming from smartphones. We have introduced the fuzzy sets to take into account uncertainty embedded in GPS data when trying to identify the position of cars within the road lanes. Moreover, we introduced a Genetic Algorithm to calibrate the fuzzy parameters in order to obtain a novel supervised clustering technique. We applied the proposed method to one intersection in the urban road network of Bari (Italy). First results reveal the effectiveness of the proposed methodology when comparing the outcomes of the proposed method with two well-known clustering techniques (Fuzzy C-means, K-means).

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Keywords: Intelligent transportation systems; Global positioning system; Positioning Accuracy; Supervised custering

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1. Introduction

The analysis of issues related to the urban movement of cars has assumed an increasingly important role in recent years. The urban traffic conditions greatly slowed down and have become congested; in fact, not only create inconveniences to car drivers for the increase in the average travel time but also make a less secure circulation on the road and increase air and noise pollution.

The development of Intelligent Transport Systems and info-mobility represent an opportunities to reduce costs and road congestion, with sustainable timing. In the era of multimedia convergence, communication, and sensing platforms, GPS-enabled smartphones are becoming an essential contributor to location-based services. These devices combine the advantages of mobile sensors mentioned earlier: low investment costs, high penetration, and high accuracy achieved by GPS receivers. In addition, GPS-enabled smartphones are able to provide accurately not only position but also speed and direction of the travel. Note that phones not only can send but also receive information. Therefore, traffic information can be delivered through this channel. Given the market penetration of mobile phones, this new sensing technology can potentially provide an exhaustive spatial and temporal coverage of the transportation network. In the mobile computing era, smartphones have become instrumental tools to develop innovative mobile context-aware systems because of their numerous sensors such as GPS, accelerometers, gyroscopes. This makes them suitable enablers to capture a wide range of contextual features, like weather and traffic conditions (Miranda-Moreno, 2015).

Real-time traffic reports are usually based on statistical methods. These methods have been also a common practice in studies that use cell phones as traffic sensors, in which the main goal has been to find the link speed or travel time estimation (Bar-Gera, 2007). Note that the aforementioned study uses cell phone antennas to obtain a cell phone position (i.e. vehicle), which is less accurate than GPS positioning. Krause et al. (2008) have investigated the use of machine learning techniques to reconstruct travel times on a graph based on sparse measurements collected from GPS devices embedded in cell phones and automobiles.

An overview of the GPS techniques is given in Skog and Handel (2009). For mapping the vehicle position in the road, sophisticated algorithms have been developed (Zhao, 2015; Fouque and Bonnifait, 2012). The usual problem in GPS positioning is that the accuracy is not within a lane-width. Therefore, solutions have to be found to get the accuracy to a lane level. Liu et al. (2017) present a recognition system for dangerous vehicle steering based on the low-cost sensors found in a smartphone, i.e. the gyroscope and the accelerometer. To identify vehicle steering maneuvers, we focus on the vehicle's angular velocity, which is characterized by gyroscope data from a smartphone mounted in the vehicle. Recently, there has been much related research on lane determination involving the use of the camera (Wang et al., 2009), Differential GPS (Moon et al., 2010), vehicle to vehicle communication (Basnayake et al., 2011), or Global Navigation Satellite System (Obst et al., 2011) as fully active sensors. All of these methods require a considerable amount of equipment to be placed in the car. Other works considered the creation of lane-level maps (Zhang and Taliwal, 2003; Chen and Krumm, 2010) and methods where the smartphone itself is fully active (Mohan et al., 2008; Biagioni et al., 2011).

Sekimoto et al. (2012) proposed a simple method for using the separation distance (offset) between a smartphone GPS and the center line on a digital road map to determine the lane position of a car.

Knopp et al. (2017) presented a methodology to map the lanes on a motorway using data collected. The methodology exploits the high accuracy and the fact that the most driving is within a lane.

Astarita et al. (2017) proposed the use of information coming from connected mobile devices (on vehicles) to regulate traffic light systems.

In this work, we present a methodology for the determination and identification of a vehicle on a road lane in proximity to a signalized road intersection, using GPS-enabled smartphones. The proposed method is based on the Fuzzy set theory (Zadeh, 1965) as it is useful in dealing with uncertainty embedded in the observed data. We have used fuzzy sets to represent the membership degree of a vehicle position to a lane. Moreover, a road reference system has been defined to process GPS track data obtained by a smartphone GPS. To find the optimal distributions, we have defined a *supervised* clustering technique to efficiently evaluate the lane positioning of a vehicle through a Genetic Algorithm.

2. The proposed method

In this section, we describe the method used to find the position of a vehicle on a lane in the proximity of any signalized road intersection. We used the GPS data recorded by smartphone devices. First, we need to define the observation area, where the main road references and the definition of the virtual sections take place. A set of base points at the roadside identifies the virtual sections. To determine the roadside starting from two sampling points A and B we used the following relation:

$$y = \frac{(y_B - y_A)(x - x_A)}{x_B - x_A} + y_A \tag{1}$$

while the equations of the relative virtual sections are:

$$y_{VS_j} = -\frac{1}{m(x - x_j)} + y_j \tag{2}$$

where $m = \frac{y_B - y_A}{x_B - x_A}$, VS_j is the virtual section j, and x_j, y_j are the coordinates of the j-th base point. Figure 1 shows the steps to obtain the input data from the acquired GPS track data.

Detect roadside through points A and B

↓

Construct virtual sections as orthogonal lines to the roadside

↓

Determine distance between each GPS tracks point and virtual sections

↓

Project each track point to the nearest virtual section and normalize its distance with respect to the lane width

Fig. 1. Steps to obtain the input data.

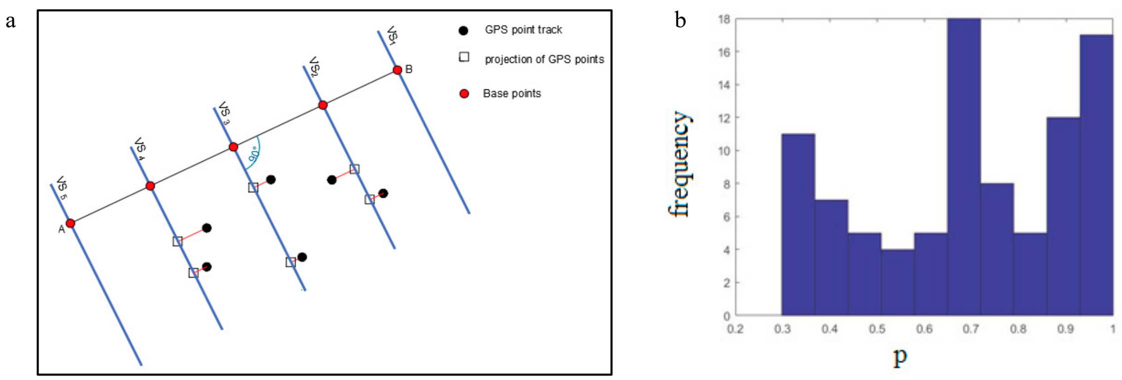


Fig. 2. (a) Construction of virtual sections and (b) the statistical trend of the recorded GPS data.

Figure 2a shows the roadside and five sections. The base points A and B have coordinates (x_A, y_A) and (x_B, y_B), used in Eq. 1 to find the roadside. Starting from these base points, we created five virtual sections, VS_1 to VS_5; the

GPS data projections on these virtual sections (square dots in Fig. 2a) have been obtained considering for each GPS point *i* (black dots in Fig. 2a) the minimum distance $d_{i,j}$ from every virtual section *VSj*, as follows:

$$i \in VS_j \ if \ d_{i,j} = min(d_{i,k}), \quad j,k = 1, \dots, n_s \tag{3}$$

where n_s is number of virtual section.
The distances from the roadside of the GPS data projections, i.e. the lateral positions of the GPS points, have been normalized with respect to the lane width.
The values of the normalized lateral positions $p_{i,j}$ of points i on a virtual section j have been calculated using the following expression:

$$p_{i,j} = \frac{\sqrt{(x_j-x_i)^2+(y_j-y_i)^2}}{D_j} \tag{4}$$

where D_j is the width of a given virtual section j.
To test our method, we considered a set of measurements carried out by a smartphone device, in a three-lanes road. Fig. 2b reports the histogram of the normalized lateral positions of surveyed points. A three normal probability distribution fits the histogram, where three high-frequency points can be observed. Each one of these points can be associated with the midpoint of a lane in the considered road.
Thus, in general, we can define the probability distribution for each virtual section j through the following expression:

$$\Phi_j(p_i) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(p_i-\mu)^2}{2\sigma^2}} \tag{5}$$

where the characteristic parameters are the mean μ and the standard deviation σ; p_i is the lateral position of the point i on the section j, as defined by Eq. 4.
Due to the uncertainty embedded in the GPS data, we considered fuzzy distributions to represent a point into a road lane. We used Gaussian-shaped Fuzzy Sets to represent a membership function Π_l of a lane l and defined as follows:

$$\Pi_{l,j}(p_i) = e^{-\frac{(p_i-\mu_{l,j})^2}{2\sigma_{l,j}^2}} \tag{6}$$

where the parameter μ_l for a lane l is the central value of the distribution, defined as:

$$\mu_{l,j} = \frac{1}{N_l}\sum_{i=1}^{N_l} p_{i,j} \tag{7}$$

where N_l is the number of normalized projections belonging to a lane l. The standard deviation $\sigma_{l,j}$ for each virtual section j is defined as follows:

$$\sigma_{l,j} = \sqrt{\frac{1}{N_l-1}\sum_{i=1}^{N_l} |p_{i,j} - \mu_{l,j}|^2} \tag{8}$$

The correct parametrization of the membership functions for each lane is a key problem to maximize the accuracy of the position identification.
The membership degree of a projection p_i (lateral position) to a function Π_l is evaluated and the associated lane C is determined as follows:

$$C(p_i) = l \ if \ \Pi_l(p_i) = \ max\{\Pi_j(p_i)\} \ , \quad 1 \le j \le n_l \tag{9}$$

where n_l is the number of lanes.
The set W of correctly identified lane positions is such that:

$$\hat{C}_i \in W \ \Leftrightarrow \hat{C}_i = C_i \tag{10}$$

where C_i is the lane associated with GPS data and $\hat{C}_i$ the value estimated by the method.

In this way, the identification error ε is defined as:

$$\varepsilon = 1 - \frac{N_c}{N_t} \tag{11}$$

where N_c is the number of correct estimations, N_t is the total number of the GPS points considered.

The objective is to determine the optimal parameters, mean μ and standard deviation σ, of the membership functions. We can consider the proposed method as a *supervised* clustering technique for uncertain GPS data. In the following, we propose a genetic algorithm for an optimal parametrization.

3. Calibration using Genetic Algorithms

In this section, we present an approach based on genetic algorithms (GA) to calibrate the parameters (σ, μ) as described above. We chose GA due to their high flexibility, robustness and global search capabilities. In particular, for each virtual section, the aim is to find the optimal parameters of the Gaussian membership function Π_l as defined through eq. 6. The objective function associated to the optimization problem is defined through the following expression:

$$max\, Z = \frac{n_c}{N} * 100 + \frac{1}{N} \sum_{\substack{i=1 \\ i \in N_c}}^{N} \sum_{l=1}^{n_l} |\Pi_{max}(p_i) - \Pi_l(p_i)| \tag{12}$$

where is n_c is the number of correct identifications, $\frac{n_c}{N}$ is the accurancy rate, i.e. the percentage of correct identifications globally made, N_c is the set of corrected estimated points, p_i is the normalized projection value on a given virtual section, $\Pi_{\max}(p_i) = \max\ \{\Pi_c(p_i)\}$, c=1,…,$n_l$.

In the proposed genetic algorithm, a chromosome has been encoded considering the parameters μ and σ. Each pair of genes represents a couple of parameters (μ, σ) related to the membership function of a lane l in a given section. The resulting encoding is reported in Figure 3.

μ_1	σ_1	…	…	μ_{n_l}	σ_{n_l}

Fig. 3. Chromosome structure of the genetic algorithm.

The optimization problem is subject to lower and upper bounds of decision variables μ and σ, respectively $0 \leq \mu \leq 1$ and $0.01 \leq \sigma \leq 0.5$.

4. Application and results

To evaluate the outcomes of the proposed method, we have considered the GPS track data relative to two main roads converging to a signalized intersection in the city of Bari (Italy). The first road consists of three lanes eastbound, while the second one consists of two lanes in the westbound.

GPS track data have been acquired using a connected vehicle equipped with an Android smartphone. The acquired database consists of 86 runs (54 on the two-lane road, 32 on the three-lane road) with 1 Hz of data acquisition frequency.

Figure 4 shows the five virtual sections (*VSs*) considered for each road, where the first section is the farthest one from the intersection stopping point. Figure 5a and 5b report the acquired GPS tracks relative to each race for each considered road. Blue points refer to the GPS points projected on each associated virtual section according to Eq. 3.

Fig. 4. Construction of virtual sections for the two-lane road.

a b

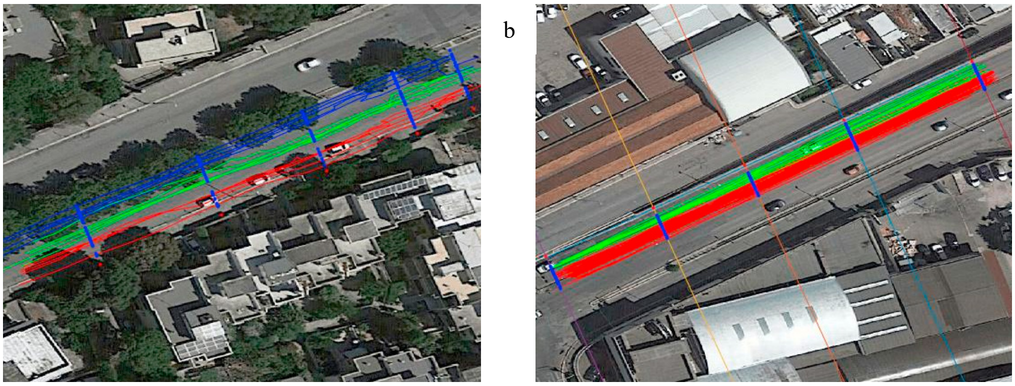


Fig. 5. The considered roads with (a) three lanes and (b) two lanes and recorded GPS tracks.

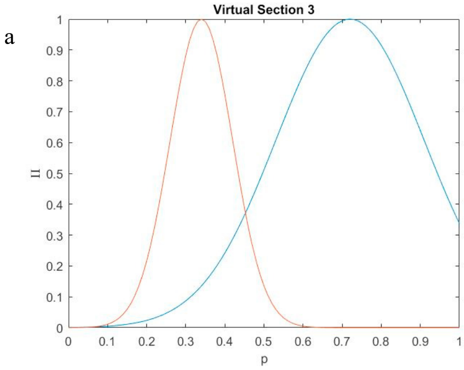
To calibrate the fuzzy parameters related to lanes' membership functions, we have used a dataset made of 50% of the overall acquired data (calibration set). The remaining 50% (validation set) has been used to validate the identification performances of the proposed method. In Table 1 and 2, the results of the calibrated parameters μ and σ of the membership function are reported for each road in correspondence of each considered virtual section. In Figure 6, an example of the resulting membership functions for one virtual section obtained by the calibration process for each road is reported. To compare the outcomes of the proposed method, two well-known clustering methods have been considered: Fuzzy C-means (FCM) and K-means. Table 3 shows the lane identification error ε obtained by the proposed method and compared with FCM and K-means. We can observe that the proposed method outperforms the other clustering techniques for both calibration and validation set.

Table 1. Resulting calibrated parameters μ and σ of the membership functions for the road with 2 lanes.

Virtual section	**Lane 1**		**Lane 2**	
	σ	μ	σ	μ
VS_1	0.19	0.69	0.13	0.27
VS_2	0.18	0.68	0.12	0.27
VS_3	0.19	0.72	0.08	0.34
VS_4	0.25	0.75	0.08	0.34
VS_5	0.27	0.79	0.08	0.34

Table 2. Resulting calibrated parameters μ and σ of the membership functions for the road with 3 lanes.

Virtual section	Lane 1		Lane 2		Lane 3	
	σ	μ	σ	μ	σ	μ
VS_1	0.18	0.25	0.14	0.61	0.08	0.85
VS_2	0.17	0.24	0.13	0.61	0.08	0.87
VS_3	0.16	0.25	0.11	0.58	0.11	0.89
VS_4	0.11	0.22	0.13	0.55	0.16	0.91
VS_5	0.11	0.28	0.08	0.55	0.16	0.77



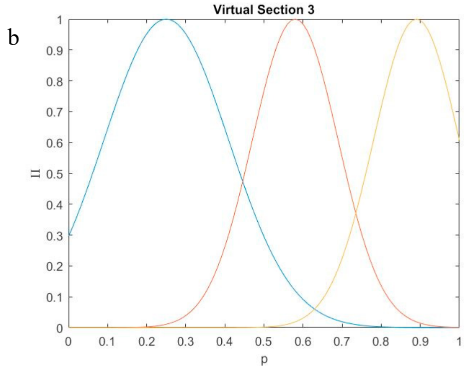


Fig. 6. Resulting membership functions related to a virtual section for (a) two-lane and (b) three-lane road.

Table 3. Comparison of the proposed method with C-means and K-means clustering techniques in terms of identification error.

ROAD	VS	Calibration set			Validation set		
		Proposed method	FCM	K-means	Proposed method	FCM	K-means
3 LANES	1	9.10%	18.20%	19.30%	8.82%	75.90%	72.99%
	2	2.30%	27.60%	28.70%	1.08%	66.25%	60.63%
	3	0.00%	29.80%	30.60%	0.00%	70.25%	62.13%
	4	0.00%	43.10%	44.00%	3.05%	56.66%	60,48%
	5	0.00%	13.30%	14.50%	9.49%	89.11%	90.57%
2 LANES	1	2.22%	12.80%	13.33%	10.07%	23.17%	26.63%
	2	4.82%	5.97%	6.02%	7.77%	12.86%	14.06%
	3	0.00%	0.00%	0.00%	3.38%	11.85%	11.12%
	4	0.00%	0.00%	0.00%	1.08%	10.68%	10.66%
	5	0.00%	5.18%	5.26%	1.97%	9.37%	10.05%

5. Conclusion

This paper presented a novel method for road lane identification of a vehicle equipped with a smartphone in correspondence of intersections. GPS data were sufficiently accurate to track a vehicle at the lane level. We proposed a supervised clustering technique based on fuzzy sets and genetic algorithms. Fuzzy sets were used to take into account uncertainty in acquired GPS data and to evaluate the membership of a car position to a road lane. To obtain an optimal identification model, the calibration of the membership functions was carried out through the Genetic Algorithms. To evaluate the outcomes of the proposed method, we considered two roads converging to a signalized intersection in the city of Bari (Italy). The results obtained by the proposed method were compared with C-means and K-means clustering techniques. Results revealed a good identification accuracy of the proposed method for both roads. As a result, the proposed method allows overcoming the problems related to the “noise” that affects the measurements, and the errors related to obstruction or reflection of GPS data. Additional studies are needed to quantify these effects more precisely and to evaluate their implications for different applications. However, this work presented the first methodology of a wider framework for road traffic assessment and control based on real-time data coming from travelers’ smartphones. In particular, future developments will concern with flow estimation and adaptive traffic signal setting optimization.

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