Transportation Research Board - 94<sup>th</sup> Annual Meeting, Paper ID: 15-4885

# Localization and driving behavior classification using smartphone sensors in the direct absence of GNSS

Constantinos Antoniou<sup>a</sup>, Vassilis Gikas<sup>a</sup>, Vasileia Papathanasopoulou<sup>a</sup>, Chris Danezis<sup>b</sup>, Athanasios D. Panagopoulos<sup>c</sup>, Ioulia Markou<sup>a</sup>, Dimitrios Efthymiou<sup>a</sup>, George Yannis<sup>d</sup>, Harris Perakis<sup>a</sup>

<sup>a</sup> School of Rural and Surveying Engineering, National Technical University of Athens <sup>b</sup> Department of Civil Engineering and Geomatics, Cyprus University of Technology

## INTRODUCTION

The objective of this research is to present a framework for the vehicle localization and monitoring and modeling of driving behavior in indoor facilities, or -more generallyfacilities where GNSS information is not available.

Several broad sources of information can be considered:

- Point measurements of vehicle crossings
- Point-to-point measurements
- Localization of vehicles equipped with some other type of sensor, interacting with an access-point or other type of infrastructure; and
- Sensors (such as accelerometers and gyroscopes) available on-board the vehicle or on nomadic devices (such as smartphones)

## LOCALIZATION TECHNOLOGIES, NEEDS AND METHODOLOGY ADOPTED

### **3D Positioning and Navigation of Vehicles for ITS**

In indoor parking garages the navigation solution may involve GNSS to get initial location information near the entrance, which is then propagated in time using other navigation sources. An overview of the most commonly used positioning sensor technologies and their typical accuracy metrics in given in Table 1.

Sensor / technique	Navigation information	Ty
GPS position GPS velocity	X, Y, Z v <sub>x</sub> , v <sub>y</sub> , v <sub>z</sub>	~10 ~0. m
pseudolites	X, Y, Z V <sub>x</sub> , V <sub>v</sub> , V <sub>z</sub>	com
UWB	X, Ý, Z	
IEEE 802.11 fingerprinting	Χ, Υ	
Bluetooth (e.g. BLE)	Χ, Υ	
RFID cell-based	Χ, Υ	depe
RFID fingerprinting	Χ, Υ	
accelerometer	a <sub>tan</sub> , a <sub>rad</sub> , a <sub>z</sub>	
gyroscope	heading φ	
Image-based	X, Y, Z	
optical sensor network	X, Y, (Z optional)	
laser	X, Y, Z	
digital compass/ magnetometer	heading φ	
barometric pressure sensor	Z	
temperature sensor	Т	
	Sensor / technique GPS position GPS velocity pseudolites UWB IEEE 802.11 fingerprinting Bluetooth (e.g. BLE) RFID cell-based RFID fingerprinting accelerometer gyroscope Image-based optical sensor network laser digital compass/ magnetometer barometric pressure sensor temperature sensor	Sensor / techniqueNavigation informationGPS position GPS velocityX, Y, Z $v_x, v_y, v_z$ pseudolitesX, Y, Z $v_x, v_y, v_z$ UWBX, Y, ZIEEE B02.11X, YIEEE fingerprintingX, YBluetooth (e.g. BLE)X, YRFID cell-based RFID fingerprintingX, Yaccelerometer gyroscope $a_{tan}, a_{rad}, a_z$ gyroscopeheading φImage-based optical sensor networkX, Y, Zdigital compass/ magnetometerheading φbarometric sensorZtemperature sensorT

Table 1: Commonly used sensor types for navigation support in ITS applications

#### Wireless Sensor Networks-Aided Indoor Positioning

The dynamic nature of the radio environment makes the employment of fingerprinting algorithms infeasible, and therefore triangulation algorithms are recommended. Rangebased positioning algorithms may use: (i) Mobile Terminal-based indoor positioning systems, (ii) Mobile Terminal-assisted indoor positioning system designs, (iii) Indoor Positioning with beacons and (iv) Indoor Positioning with moving beacons.

### Positioning Requirements in Parking Facilities and Monitoring Approach Adopted

This study concentrates on testing the capabilities and potential of sensors found in common smart mobile phones. Particularly, it attempts an initial sensor capability characterization and driving behavior classification through studying patterns in the raw data distributions. Testing focuses on acceleration and gyroscope observations.

<sup>c</sup> School of Electrical and Computer Engineering, National Technical University of Athens <sup>d</sup> Department of Transportation Planning and Engineering, National Technical University of Athens



pical accuracy

m (DGPS 1-3 m) .05 m/s, ~0.05 n/s, ~0.2 m/s

#### parable to GNSS

dm-level

3-5 m

1-2 m

ends on cell size 1-3 m

<0.03 m/s<sup>2</sup>

0.5°-3° few meters few meters cm to dm

0.5°-3°

1-3 m

0.2°-0.5° C



Figure 1 (a-b): (a) Field test trajectories (b) sensor colocation diagram

### **ASSESMENT OF NAVIGATION SOLUTION**



Figure 2 : Interpretation of sensor data

All devices involved in the test successfully detected all events. Visible changes of acceleration values of an abrupt character are observed for all recording devices and for all four speed hump locations. Notably, the excessive noise in the SPAN data is due to unsmoothed observables

## **DRIVER BEHAVIOR CLASSIFICATION ANALYSIS**

A more macroscopic analysis of the driver behavior includes the defining of the optimal number of clusters with the package "ClusterCrit", within the R software for statistical computing. The Kmeans algorithm was used. Internal indices provide insight supporting the choice of the optimal number of clusters. External indices measure the similarity between two partitions, mainly two clustering alternatives, taking into account only the distribution of the data in the different clusters.

Internal Index	Optimal number of clusters			
	NTUA-1	NTUA-2	NTUA-2	- I - I - 0.30
		(no gyros)		/sky_Lai
Ratkowsky_Lance	3	3	3	Ratkow 0.20
(rule: max)				2
Dunn	5	5	3	
(rule: max)				4500
Calinski_Harabasz	5*	2*	5/3	arabasz
(rule: max)				nski_Hå 300 − 1
Log_det_ratio	4	5	3	1200 Cali
(rule: max diff)				2



The Calinski Harabasz is the least sensitive of the indices considered. The decision rule "max" corresponds to the greatest index value, while the decision rule called "max diff" corresponds to the greatest difference between two successive slopes, i.e. to the "elbow" in the curve.

Data collection was implemented in a small indoor parking facility and segments with open spaces. Driving speed range was constrained to normal city driving speeds, whereas higher acceleration / deceleration values were pursued at straight segments. The traveled trajectory included discrete scenarios, simulation of aggressive and stressful conditions and driving a ramp inside parking garage upwards and downwards.

	Con	Comparison of partitions			
		NTUA-2			
External Index	NTUA-1	(no gyros)	NTUA-2		
czekanowski_dice	0.48	0.59	0.85		
fowlkes_mallows	0.49	0.60	0.86		
jaccard	0.32	0.42	0.74		
kulczynski	0.52	0.60	0.87		
precision	0.64	0.69	0.98		
rand	0.67	0.75	0.83		
recall	0.39	0.52	0.75		
rogers_tanimoto	0.41	0.53	0.57		
russel_rao	0.15	0.18	0.49		
sokal_sneath1	0.14	0.21	0.43		
sokal_sneath2	0.74	0.82	0.84		

Table 3 : External indices for determination of optimal number of clusters

### **Clustering results**

- Clustering with 5 clusters is crisper than with 3 clusters;
- includes essentially only left turns.



## **DISCUSSION AND FUTURE WORK**

Simulation of indoor environments, such as those considered in this research, requires challenging aspects of modeling vehicle operation at a microscopic scale in parking facilities. Behavioral aspects and the impact of stressful driving conditions are also of interest in this context. The absence of direct GNSS coverage in these applications, means that innovative approaches may be employed to the localization of the vehicles. Combinations of certain events can increase the confidence with which the localization of the vehicles; furthermore, low speeds within the facilities of interest in this research reduce the problem complexity. Finally, exploiting radio sensors is another interesting direction for localization under these conditions. There are many practical challenges that need to be addressed:

- Mobile terminal related measurements
- Wireless-link related measurements
- Different frequency bands of the wireless technologies
- Optimum placement of the access points
- Usage of multiple antennas and multi-node technologies





Clusters that overlap in terms of x-acc, are differentiated by y-acc (and vice versa); Gyros help distinguish the clusters in terms of x-acc, but lead to more overlap in y-acc;

NTUA-2 results in a better clustering in y-acc. This is due to the fact that NTUA-1

Figure 4 : Clustering results for 3 and 5 clusters