LOCALIZATION AND DRIVING BEHAVIOR CLASSIFICATION USING SMARTPHONE SENSORS IN THE DIRECT ABSENCE OF GNSS

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ABSTRACT

Global Navigation Satellite Systems (GNSS) have tremendous impact and potential in the development of Intelligent Transportation Systems (ITS) and mobility services, expected to deliver significant benefits including increasing capacity, improving safety and decreasing pollution. There are, however, situations where there might not be direct location information about the vehicles, such as in tunnels, but also in indoor facilities, such as parking garages and commercial vehicle depots. Various technologies can be used for vehicle localization in these cases, while other sensors, which are currently available in most modern smartphones, such as accelerometers and gyroscopes, can be used to directly obtain information about the driving patterns of the individual drivers. The use of multiple, diverse technologies for localization in the context of indoor and harsh environments has seen a lot of interest in the literature recently.

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 generally– facilities where GNSS information is not available. A survey of localization technologies and needs is presented, leading to the description of the adopted methodology. The case studies, using data from multiple types of sensors (including accelerometers and gyroscopes from two smartphone platforms, as well as two reference platforms), provide evidence that the opportunistic smartphone sensors can be useful in identifying events (i.e. speed-humps) and maneuvers (i.e. u-turns and sharp-turns), which can be useful in positioning the vehicles in indoor environments, when cross-referenced with a digital map of the facility. At a more macroscopic level, a methodology is presented and applied to determine the optimal number of clusters for the drivers' behavior, using a mix of suitable indices.

Keywords: Intelligent Transportation Systems (ITS), localization, indoor facilities, smartphone sensors, accelerometers, gyroscopes, driver behavior classification

INTRODUCTION

Intelligent Transportation Systems (ITS) such as Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS) have matured over the past few decades and are now at a point where they can be easily applied to many different operational scenarios. One of the main technologies that have supported this development is localization technologies, such as Global Navigation Satellite Systems (GNSS) *(1,2)*. GNSS have tremendous impact and potential in the development of ITS and mobility services, expected to deliver significant benefits including increasing capacity, improving safety and decreasing pollution *(1)*. It is now, therefore, possible to start looking at more challenging scenarios, like situations where there might not be direct location information about the vehicles, e.g. based on GNSS. Such scenarios occur not only in special structures, such as tunnels, but also in indoor facilities, such as parking garages and commercial vehicle depots, while they might even occur in dense urban areas (the so-called urban canyon phenomenon).

Most of these advanced systems rely on a simulation environment, which is initially calibrated based on available data *(3)*. However, depending on the application, it may be needed to dynamically steer and adjust the operation of the model *(4)*. Such functionality is supported by additional surveillance information, which becomes available from a multitude of sources. Depending on the nature of the tool, e.g. if it is aimed at planning/off-line or operational/real-time applications, the simulation model component may be microscopic, macroscopic, or mesoscopic (a combination of the two) *(5)*. The data requirements of these models escalate along with the level of detail of the model, from macroscopic/mesoscopic towards microscopic models. In any case, in order to be able to monitor and adjust the performance of the model, a number of observations are needed, including:

- Location and kinematics of vehicles; and
- Traffic dynamics/driving patterns of drivers.

Ideally, this information would be of high accuracy and available for all drivers/vehicles in the modeled environment. In reality, compromises need to be made. For example, there are technologies, such as point sensors (e.g. conventional loop detectors) that offer very limited information, but for the entirety of the vehicle population (assuming adequate number of sensors is positioned strategically in the network). Other technologies, such as IEEE 802.11 fingerprinting/Bluetooth localization, offer finer information, i.e. can track the vehicle location, but with an accuracy of a few meters (Table 1). Other sensors, which are currently available in most modern smartphones, such as accelerometers and gyroscopes, can be used to directly obtain information about the driving patterns of the individual driver. This information can then be used to develop insight into the driving behavior of the driving population. For example, driving patterns along different terrains and network features could be developed, allowing the operator to identify abnormal driving behavior (for the specific conditions). Furthermore, under certain conditions, this information could be used to infer the location of the vehicle (e.g. by using signals to detect special features of the route, such as speed humps).

Notwithstanding GNSS is a self-contained navigation system capable of providing absolute positions around the Earth and in all weather conditions, in areas prone to impertinent or difficult satellite signal reception it can fail. Such areas are usually found in the urban road environment, in tunnels and in large-scale, multi-storey parking facilities and depots, which are of particular interest in this study. In cases of limited satellite availability, various augmentation schemes are used to integrate additional information to provide viable location information. Such integration schemes rely either on differential GNSS *(2)*, on external sensor systems *(6)*, networked-assisted GNSS techniques *(7)*, terrain-aided approaches *(8)* or even on a combination of them. Nevertheless, despite the fact that GNSS-assisted systems can address successfully the positioning problem in many cases, the derived solution is highly influenced by the environment and operational scenario. Moreover, in the indoor environment, in which GNSS signal is entirely missing, other navigation solutions deem necessary. The use of multiple, diverse technologies for localization in the context of indoor and harsh environments has seen a lot of interest in the literature recently *(9-12)* and is considered a critical source of accurate and reliable data for the applications considered in this research.

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 generally– facilities where GNSS information is not available. In the absence of GNSS traces, it becomes important to be able to locate the vehicles through other means. Several broad sources of information can be considered:

- Point measurements of vehicle crossings (e.g. through conventional traffic counters);
- Point-to-point measurements, e.g. information collected from Bluetooth sensors;
- 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), providing information about the vehicle movement/dynamics, but not about its location directly.

These types of information can be considered complementary, as none provides a complete picture of all the vehicles' location and dynamics at any given time. Each provides a subset of information, that –when fused properly– can improve the ability of an information system to reconstruct the traffic state, which in turn could be used to develop and evaluate scenarios (e.g. in the case of emergency conditions). In this research, we focus on sensors from smartphones.

The remainder of this paper is structured as follows. A survey of localization technologies and needs is presented next, leading to the description of the adopted methodology. The setup of the case studies, using data from multiple types of sensors, is presented next, followed by a preliminary analysis of the acquired data. An assessment of the positioning solution is performed next, followed by a presentation of the driver behavior classification analysis. A concluding section discusses the main findings and provides directions for further research.

LOCALIZATION TECHNOLOGIES, NEEDS AND METHODOLOGY ADOPTED

3D Positioning and Navigation of Vehicles for ITS

Specifically, in indoor parking garages, depending on operational scenario, the navigation solution may involve GNSS to get initial location information near the entrance (or other spot of adequate satellite signal reception), which is then propagated in time using other navigation sources. Such positioning systems can be classified according to sensor technology (radio frequency, inertial, optical systems, etc.), the position fixing technique (time of arrival, round trip, time, Doppler ranging, etc.) or their performance metrics (accuracy, availability, integrity, etc.). Table 1 gives an overview of the most commonly used positioning sensor technologies and their typical accuracy metrics *(13,14)*. To ensure high accuracy and continuity in the positioning solution, multi-sensory approaches have been developed, in which the integration strategy primarily relies on the Kalman filter algorithm *(15)*. This approach has recently been extended to the collaborative navigation concept, in which the vehicles represent the nodes of a network that can exchange information to obtain an improved navigation solution *(16,17)*.

TABLE 1. Commonly used sensor types for navigation support in ITS applications (adapted from *(13)*)

	Sensor / technique	Navigation information	Typical accuracy
Radio frequency (RF)	GPS position GPS velocity	X, Y, Z v_x, v_y, v_z	~10 m (DGPS 1-3 m) ~0.05 m/s, ~0.05 m/s, ~0.2 m/s
	pseudolites	X, Y, Z v_x, v_y, v_z	comparable to GNSS
	UWB	X, Y, Z	dm-level
	IEEE 802.11 fingerprinting	X, Y	3-5 m
	Bluetooth (e.g. BLE)	X, Y	1-2 m
	RFID cell-based RFID fingerprinting	X, Y X, Y	depends on cell size 1-3 m
INS	accelerometer	a_{tan}, a_{rad}, a_z	<0.03 m/s^2
	gyroscope	heading φ	0.5^o-3^o
Optical systems	Image-based	X, Y, Z	few meters
	optical sensor network	X, Y, (Z optional)	few meters
	laser	X, Y, Z	cm to dm
Others	digital compass/ magnetometer	heading φ	0.5^o-3^o
	barometric pressure sensor	Z	1-3 m
	temperature sensor	T	0.2^o-0.5^o C

In addition to an improvement of the position performance metrics, the need for low cost solutions has led to new data collection and processing approaches that make use of vehicle in-built sensor systems *(18)* and external user portable devices such as smart mobile phones and tablets *(19)*. These devices are equipped with a wide range of sensors, from GNSS receivers through inertial sensors and magnetometers, and offer the possibility of collecting massive amount of information at low costs. Currently, extensive research is undertaken worldwide to study their performance characteristics and their potential for various ITS applications *(20-22)*.

Wireless Sensor Networks-Aided Indoor Positioning

Indoor positioning systems usually employ wireless sensor networks infrastructures in order to obtain location information of the vehicles at a predefined coordinate system. The most important and common observation metrics that are used for the development of positioning systems are the Received Signal Strength (RSS), the Time of Arrival (TOA), the Time Difference of Arrival (TDOA), the Angle of Arrival, the Doppler Ranging, and the Phase of Arrival *(23)*. This section is devoted to a general description of the operation of indoor positioning systems using wireless sensor networks. Furthermore, technical challenges and research issues on the implementation of wireless sensor networks-aided indoor parking positioning systems are discussed in the concluding section of the paper.

Indoor positioning algorithms are usually designed for specific wireless technologies of sensor networks. In the fingerprinting algorithms, the location of the mobile terminal is found by comparing a radiowave signal (usually affected by propagation phenomena), received by an access point, with a database of power values of the location under investigation. Fingerprinting algorithms include the well-known matching algorithms, k-nearest neighbour, Kalman filter, and neural networks. These algorithms have very good behaviour, if we consider a stable radio propagation environment. The dynamic nature of the radio environment makes the employment of fingerprinting algorithms infeasible, and therefore triangulation algorithms are recommended.

Range-based positioning algorithms are categorized into deterministic and probabilistic models. The deterministic models try to minimize a simple sum of differences of the real measurements and the values in the databases. In the probabilistic models, the maximum likelihood estimator is employed and in the cases where the network has some knowledge of the mobile terminal's position, the optimal estimator is the minimum square error. All these algorithms may use:

- *Mobile Terminal-based indoor positioning systems*

The position estimation is usually performed by scene analysis of signal strength characteristics.

- *Mobile Terminal-assisted indoor positioning system designs*

In order to make the load of the management smaller, there are solutions where the mobile terminals, the access points and some sniffers, which monitor the activity of the mobile terminals, cooperate in order to find the accurate location of the mobile terminals.

- *Indoor Positioning with beacons*

In wireless sensor networks, for some nodes, the system knows their exact position. These nodes are called beacons. Performing positioning algorithms the mobile terminals' location can be found using ranging or connectivity methods. The major challenge is to make efficient algorithms that use as few beacons as possible.

- *Indoor Positioning with moving beacons*

Another system design is the exploitation of moving beacons. Exploiting moving beacons, the whole system can become much more energy efficient. The relationship between mobility, navigation and positioning with mobile beacons has been studied in Galstyan et al. *(24).*

Positioning Requirements in Parking Facilities and Monitoring Approach Adopted

The choice of positioning technologies used to monitor vehicle kinematics depends on the operating environment, the type of motion and traffic modeling requirements. Vehicle motion in large-scale parking facilities and depots involves driving under geometry constraints realized usually by a grid corridor system, ramps and access to interactions. Also, vehicles normally operate at very low speeds, undertake parking maneuvers and in multi-storey facilities move between floors. Besides, modeling drivers' behavior under emergency (stressful) conditions implies vehicle motion with abrupt changes in vehicle kinematics.

These driving conditions are closely associated with certain vehicle kinematic patterns, which by extension define sensor positioning characteristics. For instance, positions derived based on accelerometer measurements cannot be very reliable at slow speeds as such, whereas their distributions at a macroscopic view can be very useful indeed. Similarly, rapid changes in the vertical datum (such those encountered when moving between floors or driving through speed humps) can be detected using magnetometers. Notably, the same parameters can be detected from gyroscope (angular rate changes) measurements, in which case the latter can serve for validation purposes.

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. To evaluate smartphone performance, a high and a tactical grade accuracy GNSS/IMU (Inertial Measurement Unit) system are collocated with test smartphones to allow comparisons between individual sensors.

CASE STUDIES SETUPS AND DATA ACQUISITION

Two experiments were carried out at the National Technical University Athens (NTUA) campus, implementing two driving scenarios in mixed (outdoor / indoor) environments. At data pre-analysis stage, the main objectives were to: (a) assess the quality of the raw data recorded by all sensors, both indoors and outdoors, and (b) evaluate the ability of smartphones to detect specific driving events, typically encountered in operations within parking facilities. While the core objective of this research relates to indoor spaces, in these experiments we operate in a mixed indoor/outdoor environment. The main reason for this is that we exploit GNSS coverage to visualize the data (e.g. trajectories) and verify the accuracy of the opportunistic sensors that we use (e.g. smartphone sensors) against the higher accuracy equipment. Another reason for this is that the environments of interest sometimes offer partial GNSS coverage (e.g. accesses to parking facilities or depots, or open areas in an predominantly covered facility). In any case, specific care is given to ensure that no information, that would otherwise not be available in an indoor environment, is used in the core parts of the procedure.

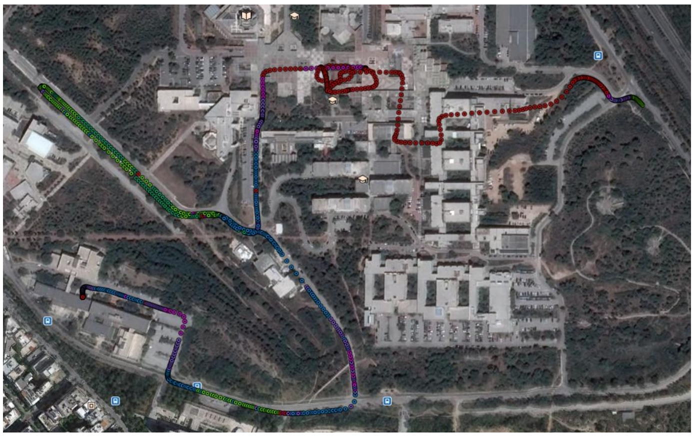
Moreover, the navigation data obtained from all sensors were grouped separately for the along-track, lateral and vertical directions to study individual phenomena pertaining to certain types of motion, such as stressful driving (associated with sudden changes in x, y-acceleration) and the detection of traffic humps (associated with changes in z-acceleration). Finally, in an attempt to detect and identify driver profile characteristics (e.g. aggressiveness) each experiment was conducted employing different drivers. In the interest of space economy, the setup of the two experiments is presented in parallel next and some aspects are not fully described.

Field tests' setup

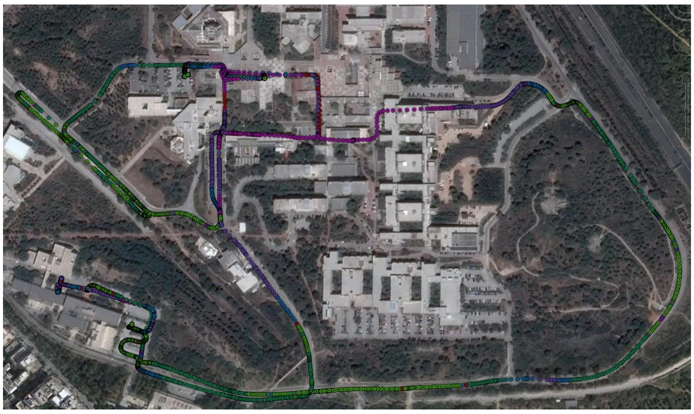
The objective of the first, preliminary experiment (NTUA-1) was to assess the quality of raw acceleration data obtained by smartphones and their potential for use in traffic simulation models. Data collection was carried out in March 27, 2014, driving a total distance of about 2.5 km long for a time span of 12 min. The traveled path included a small indoor parking facility and segments with open spaces (Figure 1(a)). Data acquisition was performed using two contemporary smartphone units: an Apple iPhone 5 and a HTC One S. Also, a NovAtel SPAN® system consisting of a geodetic grade GNSS receiver (NovAtel ProPak-V3™) and a tactical grade IMU (iMAR IMU-FSAS™) was employed to provide the vehicle's reference trajectory. The latter offers a nominal RMS acceleration accuracy of $\pm 0.03 m/s^2$.

Driving speed range was constrained to normal city driving speeds, whereas higher acceleration / deceleration values were pursued at straight segments. All sensors were collocated, aligned to the vehicle body frame and fixed onboard an on-purpose built platform on the vehicle roof. Sensor settlement is illustrated in Figure 1(c); note that the XSENS (situated in the top left of this subfigure) was not present in this experiment. Sensor relative positions with respect to the reference IMU were accurately determined by means of a dimensional survey. In the case of smartphones, data acquisition was performed using third-party software (mobile apps). Namely, SensorLog and IMU+GPS-Stream apps enabled the iPhone 5 (iOS7) and the HTC One S (Android 4.4.1) to record acceleration readings at 10Hz and 65Hz respectively. It is noted that the XSENS system was not present in this first field test. The events and scenarios simulated along the traveled path were documented and illustrated in Table 2(a).

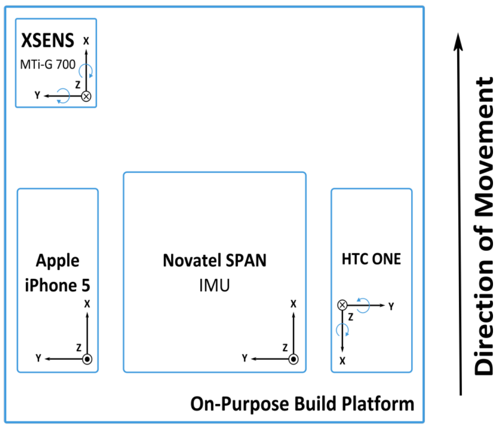
The second experiment (NTUA-2) took place in June 12, 2014. This experiment aimed both at collecting a relatively larger dataset, as well as at processing additional observable types, namely vehicle angular velocities (gyro measurements). The traveled trajectory included discrete scenarios, such as performing a limited number of parking maneuvers outdoors and indoors, simulation of aggressive and stressful conditions and driving a ramp inside a parking garage upwards and downwards. Furthermore, attention was paid so that the test vehicle traveled at relatively long periods in closed spaces to realize the indoor environment. Data were acquired driving a total distance of approximately 4.4 km spanning a time period of 20 min (Figure 1(b)). In addition to the NovAtel SPAN® system, a high-quality GPS/IMU system (XSENS MTi-G-700) was used to provide a combined output of acceleration, angular velocity, attitude and heading readings at a sampling rate 400 Hz. The MTi-G-700 was positioned onboard the same platform used in the preliminary experiment, as seen in the top left of Figure 1(c). In terms of smartphone data collection, both the iPhone 5 and the HTC One S logged acceleration, gyro, attitude and heading readings, using the SensorLog software operating at 10 Hz. The events of specific interest were logged manually and outlined in Table 2(b).



(a) NTUA-1



(b) NTUA-2



(c) Sensor colocation diagram

FIGURE 1: Field test trajectories (from NovAtel SPAN®: (a) NTUA-1, (b) NTUA-2) and (c) sensor colocation diagram (XSENS sensor, in the top-left, only used in NTUA-2)

TABLE 2. Event documentation for field tests: (a) NTUA-1, (b) NTUA-2

Event type (NTUA-1)	start time (h:m:s)	end time (h:m:s)	duration (h:m:s)
speed hump 1	15:07:47	15:07:48	0:00:01
speed hump 2	15:07:59	15:08:00	0:00:01
speed hump 3	15:08:15	15:08:16	0:00:01
speed hump 4	15:08:28	15:08:29	0:00:01
abrupt acceleration and deceleration	15:08:41	15:09:29	0:00:48
maneuvers	15:10:33	15:11:00	0:00:27
indoor ramp (upward direction)	15:12:32	15:12:43	0:00:11
uphill (upward direction)	15:13:04	15:13:25	0:00:21

(a) Events of interest during experiment NTUA-1

Event type (NTUA-2)	start time (h:m:s)	end time (h:m:s)	duration (h:m:s)
parking in open space	15:21:41	15:21:59	0:00:18
maneuvers	15:21:59	15:22:42	0:00:43
speed hump 1	15:22:43	15:22:44	0:00:01
speed hump 2	15:22:57	15:22:58	0:00:01
speed hump 3	15:23:17	15:23:18	0:00:01
speed hump 4	15:23:33	15:23:35	0:00:02
closed space (entrance/exit)	15:24:10	15:24:26	0:00:16
parking in open space (administration)	15:24:32	15:24:58	0:00:26
closed parking space (entrance)	15:25:03	--	--
parking in closed space	15:25:11	15:25:35	0:00:24
closed ramp (driving upwards)	15:25:57	15:26:04	0:00:07
closed space (exit)	15:26:04	--	--
alignment (acceleration & deceleration)	15:27:14	15:28:38	0:01:24
closed turn	15:28:38	15:28:41	0:00:03
closed parking space (entrance)	15:29:09	--	--
parking in closed space	15:29:30	15:29:49	0:00:19
closed ramp (driving upwards)	15:30:30	15:30:38	0:00:08
maneuver in closed space	15:31:12	15:31:24	0:00:12
closed ramp (driving upwards)	15:31:24	15:31:29	0:00:05
speed hump 5	15:32:22	15:32:23	0:00:01
speed hump 6	15:32:37	15:32:38	0:00:01
speed hump 7	15:33:32	15:33:33	0:00:01
speed hump 8	15:33:44	15:33:45	0:00:01

(b) Events of interest during experiment NTUA-2

ASSESSMENT OF NAVIGATION SOLUTION

Raw data acquisition from smartphone navigation sensors of variant characteristics is not a trivial task. This is because datasets include raw observables of a multitude of sensors collected at different time spans and different sampling rates. Furthermore, the performance of data collection apps depends heavily on smartphone hardware (e.g. CPU, RAM, storage) and operating system specifications. Also, system or user services that run concurrently in the background may cause extra performance penalties and raise latency issues that may result even to temporary lack of app responsiveness. Latency in data time-stamping will cause time drifts, which in turn may severely affect the microscopic analysis of sensor readings and potentially influence their distribution characteristics at a more macroscopic scale. Ergo, data resampling and synchronization were addressed prior to data analysis. Initially, all sensor records were resampled to 10Hz, the lowest sampling rate amongst the sensors used. To achieve sensor synchronization and mitigate potential drifts, all datasets were cross-compared with the reference dataset obtained using the NovAtel SPAN® system.

Navigation Data Assessment

NTUA-1: The standardized dataset comprises 7311 records per sensor corresponding to a time span of 12 min (15:01:30 – 15:13:41). Table 3(a) shows the acceleration statistics computed for all recording devices. Clearly, a relatively good agreement among all units is evident. However, a significant (132%) difference was observed in the standard deviation obtained for the HTC One S (±1.35m/s^2) and the SPAN system (±0.58m/s^2) in the vertical axis. Time-series analysis of HTC One S acceleration values revealed spikes at irregularly-spaced times in all three components. This phenomenon is more evident in the z-acc (acceleration across the z-axis) component, contributing to a higher standard deviation value. In effect, it appears that z-acc takes instantly a near zero value that immediately afterwards drops to its normal level. This bias is unique to the HTC One S smartphone and is attributed to data collection software issues, suggesting that data acquisition software can be critical for further analysis. This issue was resolved for the subsequent experiments, including NTUA-2 below.

NTUA-2: In total, 11951 epochs of data per sensor were processed spanning a time period of 20 min (18:16:50 – 18:36:45). Table 3(b) shows the acceleration statistics obtained for all sensors. Similarly to NTUA-1, test smartphone devices generally agree with the SPAN system. Besides, the HTC One S shows a more consistent logging behavior compared to the previous experiment, which is attributed to the change of data acquisition software (i.e., SensorLog from IMU+GPS-Stream). One thing to note is the difference (118%) found between the standard deviation of the XSENS z-acc (±0.83 m/s^2) and its corresponding value for the reference sample (±0.38 m/s^2). This is potentially due to the ability of XSENS to log readings on a wider acceleration range (±15 g) compared to other sensors (up to ±5 g). A noticeable difference (26%) can also be seen for the case of the x-acc.

Table 3(c) includes the statistics obtained for the angular velocity measurements for all sensors. In a similar manner to accelerations, smartphone-derived gyro measurements generally agree with the higher quality XSENS and SPAN observables. However, iPhone readings deviate from other units resulting into significant difference from SPAN in the mean x- and z-gyro values. Interestingly, no significant differences are observed in the corresponding standard deviations and max / min values, suggesting a bias in the iPhone measurements, the source of which remains undetected.

TABLE 3. Statistics of collected data (accelerations and angular speeds)

device	x-acc				y-acc				z-acc			
	min	max	mean	σ	min	max	mean	σ	Min	max	mean	σ
Apple iPhone 5	-6.66	4.45	0.63	0.98	-6.31	8.48	0.14	1.18	-26.50	-4.71	-9.81	0.57
HTC One S	-6.91	4.62	0.57	1.01	-5.89	5.90	-0.23	0.96	-15.24	0.00	-9.51	1.35
NovAtel SPAN	-6.87	8.21	0.61	1.05	-6.58	7.24	-0.16	1.01	-16.80	-0.33	-9.77	0.58

(a) NTUA-1 accelerations (m/s^2)

sensor	x-acc				y-acc				z-acc			
	min	max	mean	σ	min	max	mean	σ	min	max	mean	σ
Apple iPhone 5	-3.91	5.12	-0.28	0.72	-4.03	6.84	0.28	0.93	-13.12	-7.41	-9.88	0.32
HTC One S	-4.90	6.97	0.13	0.77	-4.08	7.25	0.39	0.96	-14.46	-4.85	-9.73	0.39
XSENS	-6.26	7.26	-0.13	0.95	-4.68	7.46	0.21	1.00	-21.00	-3.12	-9.81	0.83
NovAtel SPAN	-4.70	5.52	0.04	0.75	-4.08	7.05	0.24	0.94	-14.17	-3.73	-9.79	0.38

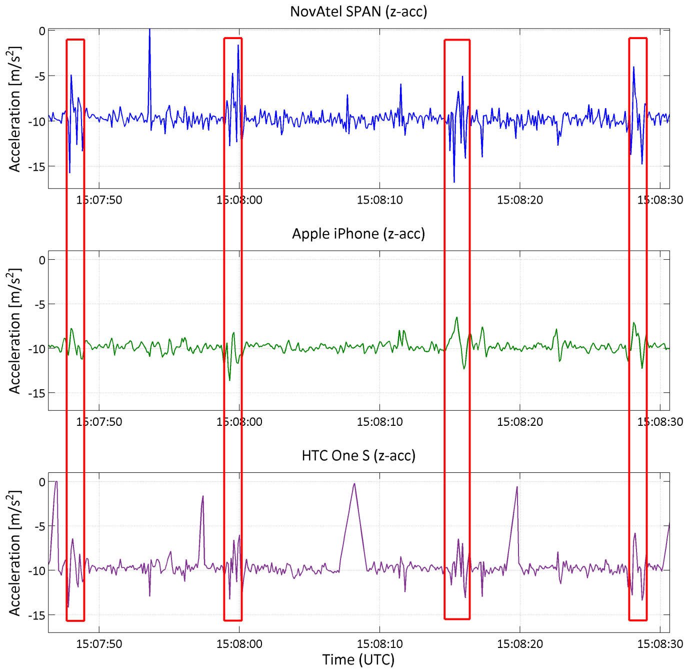
(b) NTUA-2 accelerations (m/s2)

device	x-gyro				y-gyro				z-gyro			
	min	max	mean	σ	min	max	mean	σ	min	max	mean	σ
Apple iPhone 5	-14.61	19.89	1.91	1.69	-10.24	15.32	-0.10	1.15	-38.27	41.31	-1.20	8.97
HTC One S	-20.02	15.83	0.04	1.87	-15.40	14.18	0.03	1.32	-37.13	42.76	-0.15	9.05
XSENS	-24.73	21.38	-0.10	2.16	-20.36	18.83	0.01	2.07	-37.93	43.87	-0.13	9.17
NovAtel SPAN	-20.89	16.27	0.00	2.03	-15.98	16.75	0.02	1.60	-36.36	41.79	-0.15	8.90

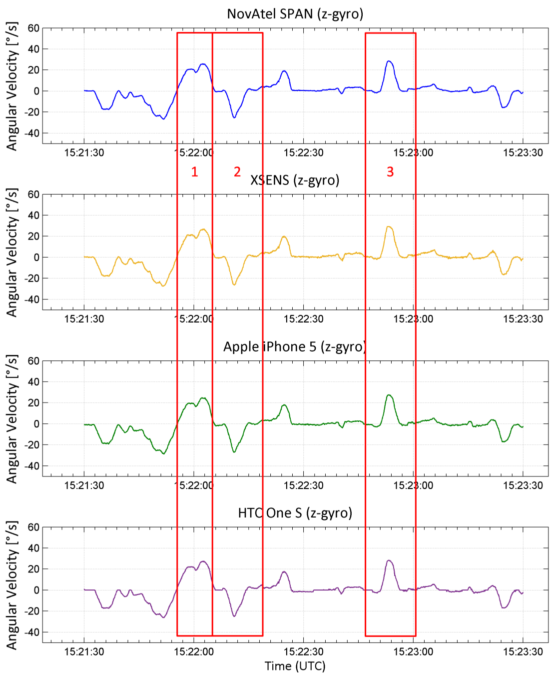
(c) Angular velocity data for NTUA-2 test (deg/s)

Microscopic analysis

In brief, all devices involved in the test successfully detected all events. For instance, in order to assess the ability of smartphones to detect speed humps, their locations were marked (red frames) on the z-acc plots as shown in Figure 2(a) based on their time logs (Table 2(a)). Clearly, 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.



(a) NTUA-1: Speed hump detection example based on z-acc measurements (spikes in the bottom/HTC One S subfigure are due to the logging issue discussed in the text, and resolved for NTUA-2)



(b) NTUA-2: Smartphone z-gyro sensor readings for a subset of NTUA-2 test

FIGURE 2. Interpretation of sensor data

Regarding analyzing driving scenarios of particular interest, a case of steep turn and U-turn maneuvers are considered in this study (Figure 2(b)). The selected section includes two U-turn maneuvers (area 1 and 2) and a steep left turn (area 3). The two U-turn maneuvers were driven deliberately at different speeds; the first one (area 1) in a faster pace compared to the second one (area 2). From Figure 2(b) it is apparent that all devices detected clearly these events. The considerably shorter time length of the first maneuver compared to the second one indicates a faster change in the heading component. During a U-turn maneuver the vehicle's heading changes by 180^{o}. This fact is also recognized in the data since the angular velocity sign changes from positive to negative (area 1) and vise-versa (area 2).

DRIVER BEHAVIOR CLASSIFICATION ANALYSIS

We now turn our attention to a more macroscopic analysis of the driver behavior, through clustering of the data. The k-means algorithm *(25,26)* was used; however, this algorithm does not provide a way to determine the optimal number of clusters. In order to determine the optimal clustering, we considered a number of indices, with the help of the recently developed package "ClusterCrit" *(27),* within the R software for statistical computing *(28)*. The ClusterCrit package provides the calculation of several so-called internal and external indices. Internal indices provide insight supporting the choice of the optimal number of clusters. On the other hand, 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. Therefore, the larger the value of the index, the more similar two clustering results are.

Figure 3(a) presents the number of clusters determined as optimal by each internal index *(27)*. The Calinski Harabasz is the least sensitive of the indices considered. While the process does not converge to a single optimal number of clusters, it is very likely that the range of clusters for this application and these datasets is in the range between 3 and 5. The sensitivity of the results to the number of clusters is shown in Figure 3(c). Different decision rules apply to each index. The decision rule "max" corresponds to the greatest index value, while the decision rule called "max diff" correspond to the greatest difference between two successive slopes, i.e. to the "elbow" in the curve.

External indices were then applied to the data series in order to compare the clustering results between 3 and 5 clusters (Table 3(b)). The general concept is that the indices measure the degree to which points move across clusters, as the number of clusters increases. For instance, the Fowlkes–Mallows index could be evaluated based on the number of points that are common or uncommon in the two hierarchical clustering options. We may conclude that for NTUA-2, and especially for the richer information case including gyros, the clustering between 3 and 5 clusters seem to be more similar. This could be explained by the fact that more data may allow a more accurate clustering, even with 3 clusters.

In order to develop deeper insight into the clustering results, clustering results for 3 and 5 clusters are presented in Figure 4. Z-axis acceleration is not presented, as there was no distinct differentiation in them. Several observations can be made:

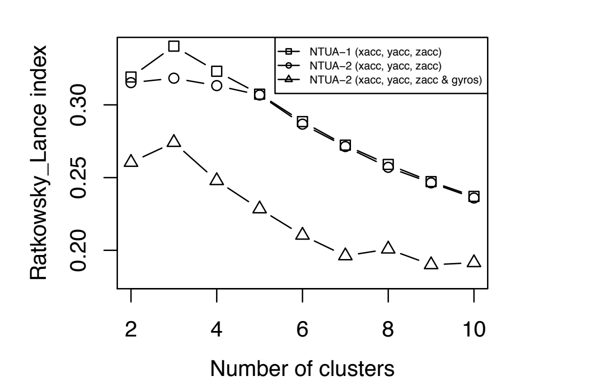
- Clusters that overlap in terms of x-acc, are differentiated by y-acc (and vice versa);
- Gyros help distinguish the clusters in terms of x-acc, but lead to more overlap in y-acc;
- Clustering with 5 clusters is crisper than with 3 clusters;
- NTUA-2 results in a better clustering in y-acc. This is due to the fact that NTUA-1 includes essentially only left turns.

Internal Index	Optimal number of clusters		
	NTUA-1	NTUA-2 (no gyros)	NTUA-2
Ratkowsky_Lance (rule: max)	3	3	3
Dunn (rule: max)	5	5	3
Calinski_Harabasz (rule: max)	5*	2*	5 / 3
Log_det_ratio (rule: max diff)	4	5	3

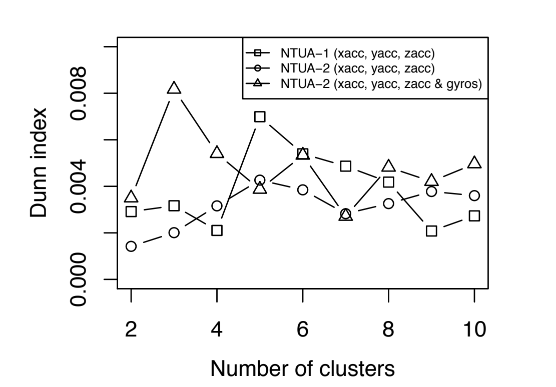
(a) Choice of the optimal number of clusters according to internal indexes
*not sensitive

	Comparison of partitions		
External Index	NTUA-1	NTUA-2 (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

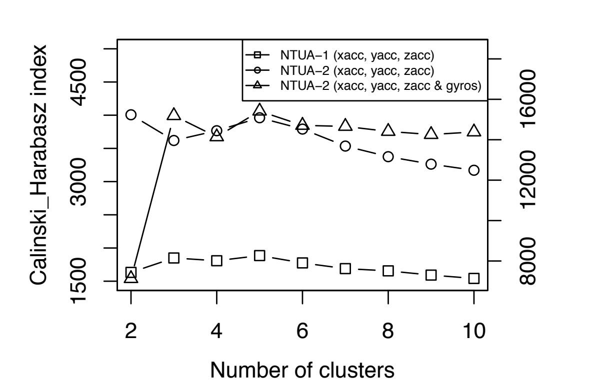
(b) Comparison of partitions (3 and 5 clusters)



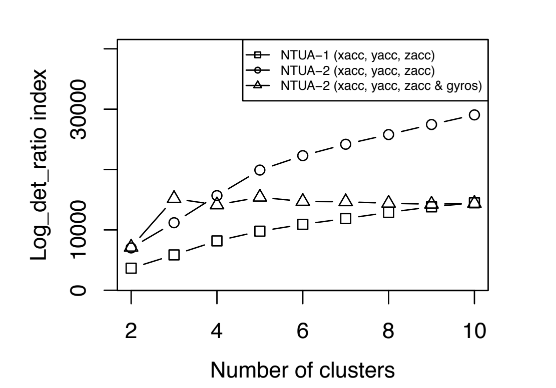
Ratkowsky_Lance



Dunn



Calinski_Harabasz (first two data-series on first y-axis, third data series on secondary y-axis)



Log_det_ratio

(c) Visual presentation of sensitivity of internal indices to number of clusters

FIGURE 3. Internal and external indices for determination of optimal number of clusters

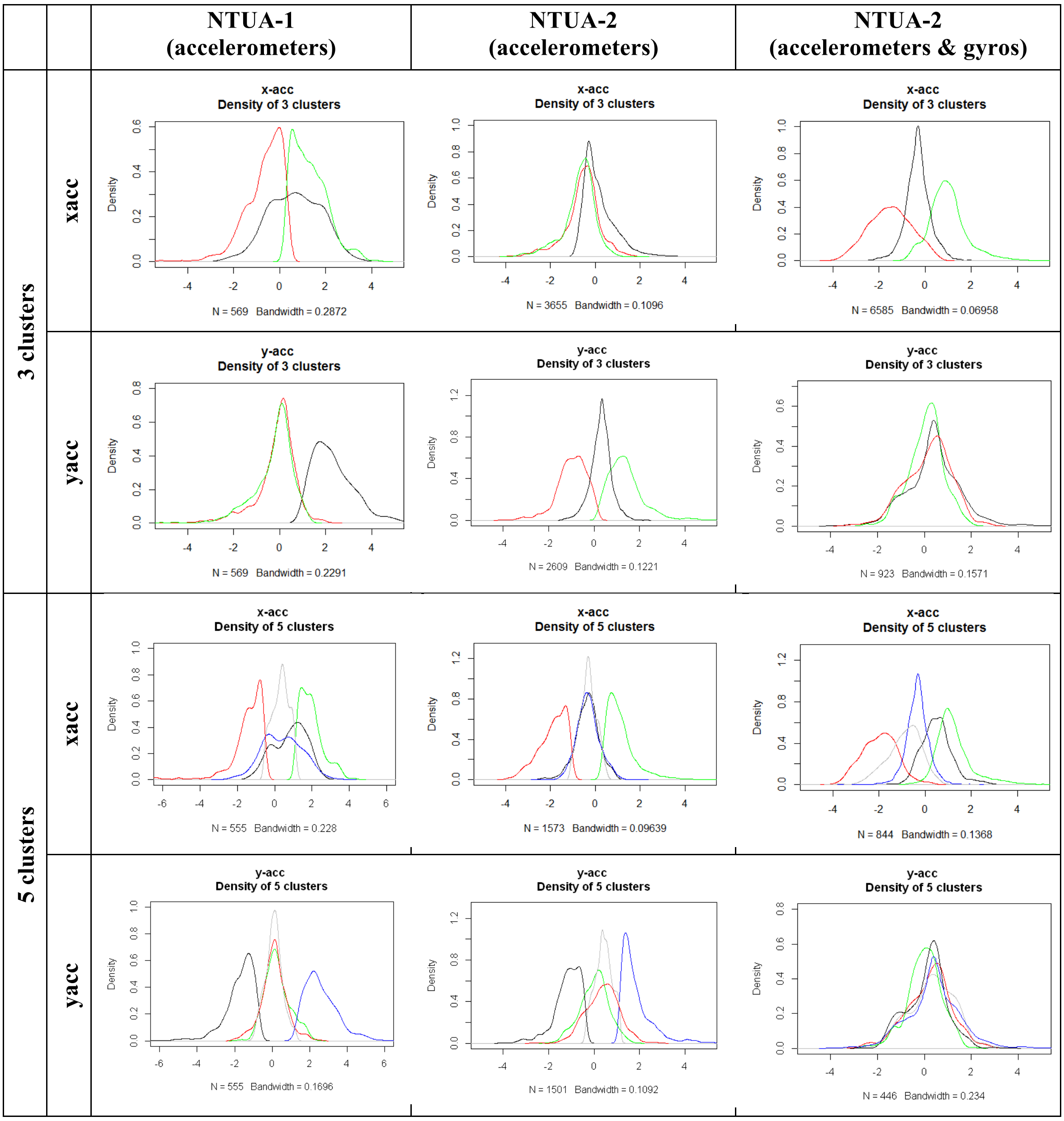


FIGURE 4. Clustering results for 3 and 5 clusters

DISCUSSION AND FUTURE WORK

ITS applications are taking an increasing role in traffic management. Traffic simulation, a mature field with several decades of development, is playing a key role in these developments. While some aspects can be assumed to be at a level, where most challenges have been overcome, there are still aspects that remain unsolved. For example, traffic simulation of mixed networks at conditions close to or exceeding capacity are still a challenging endeavor. Similarly, modeling low-speed traffic is also a challenging task (often leading to underestimation of the capacity), while parking maneuvers and their impact on the following/opposing vehicles (see e.g. *(29)*) are aspects, in which modeling can be improved.

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, which combine a number of restrictions along the state-of-the-art of traffic modeling and simulation, i.e. complex geometry, congested conditions, and very low speeds. It is possible that gap-acceptance and merging models that are formulated/estimated for general traffic will perform poorly, when applied to modeling traffic facilities. Flexible, data driven models *(e.g. 30,31)* are not bound by rigid functional forms and limits in the data that they can exploit, and therefore may be more suitable to the application of such situations.

Behavioral aspects and the impact of stressful driving conditions are also of interest in this context. Other aspects, such as privacy aspects and the willingness of the travelers to partly relinquish it in exchange for better services *(32, 33)* are also relevant, as often the technical solutions are available, but acceptance is limited.

The absence of direct GNSS coverage in these applications, means that innovative approaches may be employed to the localization of the vehicles. For example, detection of speed humps and maneuvers, such as u-turns/sharp turns, can be useful in this direction, as they could be then cross referenced with digital maps of the facilities to estimate the possible location of the vehicle. Furthermore, specific patterns on the z-axis acceleration could also be used to relate vehicle maneuvers to ramps between floors. Combinations of such 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, in this research we have focused on smartphones sensors; exploiting radio sensors is another interesting direction for localization under these conditions. It is, however, important to recognize that the indoor parking radio environment is very different from other indoor environments and prerequisite for the design for a successful positioning application is the identification of an optimal trade-off between reliability and complexity. There are many practical challenges that need to be addressed by industry and academia in this field. Here we briefly present some of them:

- *Mobile terminal related measurements:* there is heterogeneity of the wireless cards of the mobile terminals and consequently there are differences in the estimated values of RSS and biases in the whole procedure of indoor positioning.
- *Wireless-link related measurements:* there is time-varying nature of the wireless channel introduced as a result of the motion of the vehicles, the humans, the fact the mobile terminal is inside the vehicle, etc. Another problem is the channel dispersion of the signal that is caused by various effects of propagation especially in the time and frequency domains.
- *Different frequency bands of the wireless technologies,* the various technologies operate in many frequency bands (2.4GHz, 5.2GHz, 5.8GHz, 28GHz, 60GHz, etc.) that confront different propagation phenomena.
- *Optimum placement of the access points:* it strongly depends on the indoor environment, the building materials, the number of vehicles, the walls, the floors, etc. It is important in order to optimize the coverage and the connectivity of the access points.
- *Usage of multiple antennas and multi-node technologies:* large-scale MIMO (multiple-input and multiple-output) techniques will increase the accuracy of the indoor positioning system. However, their deployment in current systems will also increase the complexity.

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