Localization and Driving Behavior Classification with Smartphone Sensors in Direct Absence of Global Navigation Satellite Systems

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Global navigation satellite systems have tremendous impact and potential in the development of intelligent transportation systems and mobility services and are expected to deliver significant benefits, including increased capacity, improved safety, and decreased pollution. However, there are situations in which there might not be direct location information about vehicles, for example, in tunnels and in indoor facilities such as parking garages and commercial vehicle depots. Various technologies can be used for vehicle localization in these cases, and other sensors that are currently available in most modern smartphones, such as accelerometers and gyroscopes, can be used to obtain information directly about the driving patterns of individual drivers. The objective of this research is to present a framework for vehicle localization and modeling of driving behavior in indoor facilities or, more generally, facilities in which global navigation satellite system information is not available. Localization technologies and needs are surveyed and the adopted methodology is described. The case studies, which use 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 obstacles (e.g., speed humps) and maneuvers (e.g., U-turns and sharp turns). These data, when cross-referenced with a digital map of the facility, can be useful in positioning the vehicles in indoor environments. At a more macroscopic level, a methodology is presented and applied to determine the optimal number of clusters for the drivers' behavior with a mix of suitable indexes.

Intelligent transportation systems (ITS) such as advanced traveler information systems and advanced traffic management systems 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; they are expected to deliver significant benefits including increased capacity, improved safety, and decreased pollution (*1*). Therefore, it is now possible to start looking at more challenging scenarios, like situations in which there might not be direct location information about the vehicles, for example, 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; 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 on the basis of available data (*3*). However, depending on the application, it may be necessary 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–offline or operational–real-time applications), the simulation model component may be microscopic, macroscopic, or mesoscopic (or 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 toward microscopic models. In any case, in order to be able to monitor and adjust the performance of the model, the following observations are needed:

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

Ideally, this information would be of high accuracy and available for all drivers and 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 information that is very limited but for the entire vehicle population (assuming that an adequate number of sensors is positioned strategically in the network). Other technologies, such as IEEE 802.11 fingerprinting and Bluetooth localization, offer finer information; they can track the vehicle location but with an accuracy of a few meters (Table 1). Other sensors that are currently available in most modern smartphones, such as accelerometers and gyroscopes, can

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TABLE 1 Commonly Used Sensor Types for Navigation Support in ITS Applications (*6*)

Sensor or Technique	Navigation Information	Typical Accuracy
Radio frequency (RF)		
GPS position	*X*, *Y*, *Z*	~10 m (DGPS 1–3 m)
GPS velocity	v_x, v_y, v_z	~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	*X*, *Y*	Depends on cell size
RFID fingerprinting	*X*, *Y*	1–3 m
INS		
Accelerometer	a_{tan}, a_{rad}, a_z	<0.03 m/s^2
Gyroscope	Heading φ	0.5°–3°
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°–3°
Barometric pressure sensor	*Z*	1–3 m
Temperature sensor	*T*	0.2°C–0.5°C

NOTE: *X*, *Y*, and *Z* = geocentric Cartesian coordinates; DGPS = differential global positioning system; UWB = ultrawide-band; BLE = Bluetooth low energy; RFID = radio frequency identification; INS = inertial navigation system.

be used to obtain information directly 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; these patterns would allow the operator to identify abnormal driving behavior for 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).

Although GNSS are self-contained navigation systems capable of providing absolute positions around the earth and in all weather conditions, in areas prone to difficult satellite signal reception, they can fail. Such areas are usually found in the urban road environment in tunnels and in large-scale, multistory 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 on differential GNSS (*2*), external sensor systems (*7*), networked-assisted GNSS techniques (*8*), terrain-aided approaches (*9*), or even on a combination of them. Nevertheless, despite the fact that GNSS-assisted systems can address the positioning problem successfully in many cases, the derived solution is highly influenced by the environment and operational scenario. Moreover, in the indoor environment, in which GNSS signals are entirely missing, other navigation solutions are deemed necessary. The use of multiple, diverse technologies for localization in the context of indoor and harsh environments has been of much interest in the literature recently (*10–13*) 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 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, such as 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 onboard the vehicle or on nomadic devices (such as smartphones), providing information about the vehicle movement and dynamics but not directly about its location.

These types of information can be considered complementary, since none provides a complete picture of the location and dynamics of all the vehicles 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; this reconstruction in turn could be used to develop and evaluate scenarios (e.g., in the case of emergency conditions). In this research, the focus is on sensors from smartphones.

LOCALIZATION TECHNOLOGIES, NEEDS, AND METHODOLOGY ADOPTED

Three-Dimensional Positioning and Navigation of Vehicles for ITS

In indoor parking garages, depending on the operational scenario, the navigation solution may involve GNSS to get initial location information near the entrance (or other spot of adequate satellite signal reception); this information is then propagated in time by 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 (*6, 14*). To ensure high accuracy and continuity in the positioning solution, multisensory approaches were developed in which the integration strategy relies primarily 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*).

In addition to an improvement in the position performance metrics, the need for low-cost solutions has led to new data collection and processing approaches that use vehicle built-in 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 a massive amount of information at low cost. Currently, extensive research is being undertaken worldwide to study their performance characteristics and their potential for various ITS applications (*20–22*).

Indoor Positioning Aided by Wireless Sensor Networks

Indoor positioning systems usually employ wireless sensor network infrastructure in order to obtain vehicle location information at a predefined coordinate system. The most important and common observation metrics used for the development of positioning systems are the received signal strength, the time of arrival, the time difference of arrival, the angle of arrival, the Doppler ranging, and the phase of arrival (*23*). A general description of the operation of indoor positioning systems using wireless sensor networks is given in this section. Technical challenges and research issues on the implementation of indoor parking positioning systems aided by wireless sensor networks are discussed in the concluding section.

Indoor positioning algorithms are usually designed for specific sensor network wireless technologies. 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 neighbors, Kalman filter, and neural networks. These algorithms have very good behavior if a stable radio propagation environment is considered. 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 when 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,
- Mobile terminal–assisted indoor positioning system designs,
- Indoor positioning with beacons, and
- Indoor positioning with moving beacons (*24*).

Positioning Requirements in Parking Facilities and Monitoring Approach Adopted

The choice of positioning technology 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 geometric 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 multistory 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 from accelerometer measurements cannot be very reliable at slow speeds as such, whereas their distributions in a macroscopic view can be very useful indeed. Similarly, rapid changes in the vertical datum (such as those encountered when moving between floors or driving over speed humps) can be detected by using magnetometers. The same parameters can be detected from gyroscope (angular rate change) measurements, in which case the parameters can serve for validation purposes.

This study concentrates on testing the capabilities and potential of sensors found in common smart mobile phones. In particular, an initial sensor capability characterization and driving behavior classification are attempted through studying patterns in the raw data distributions. Testing focuses on acceleration and gyroscope observations. To evaluate smartphone performance, a system with a high and tactical-grade accuracy GNSS and inertial measurement units (IMUs) is collocated with test smartphones to allow comparisons between individual sensors.

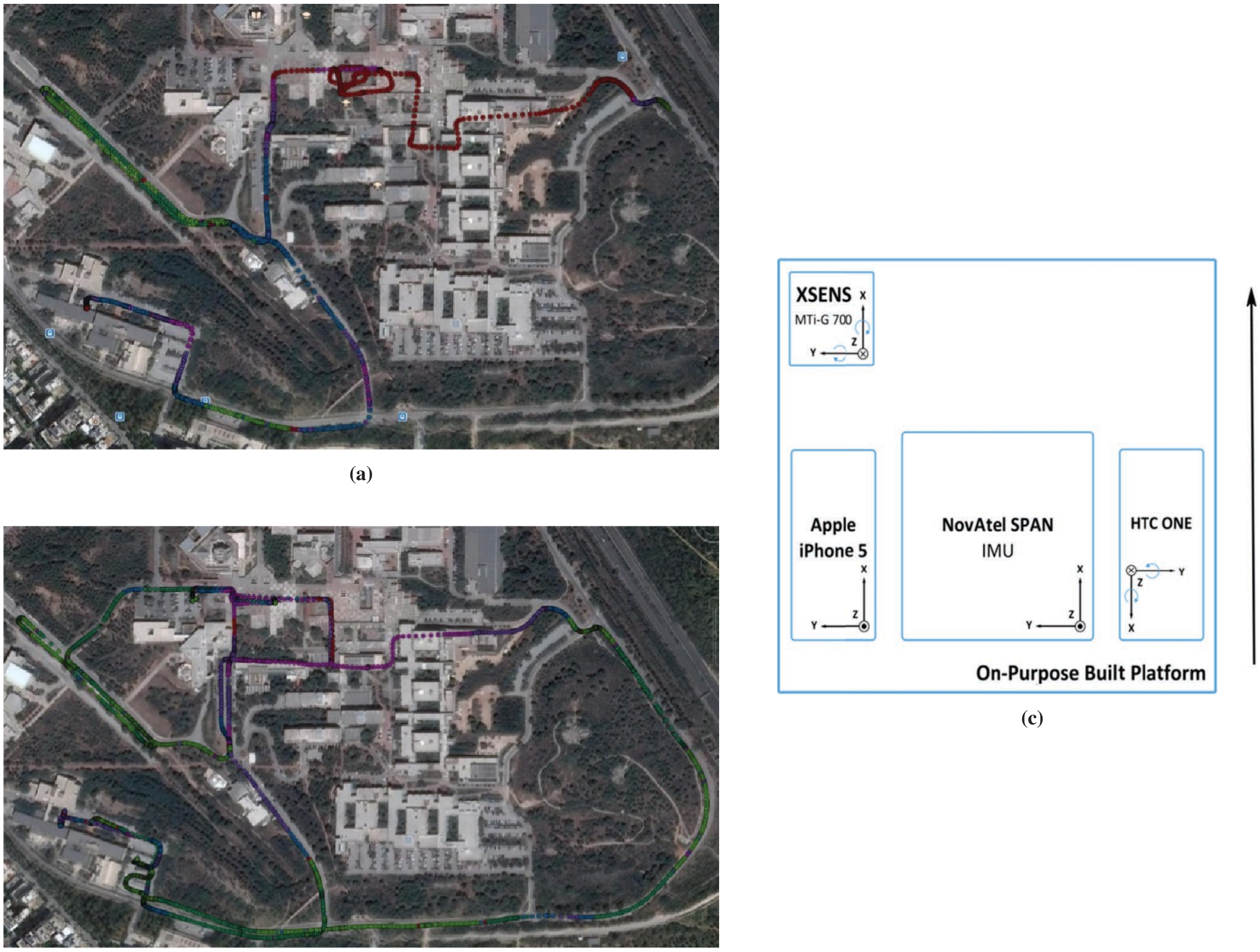
CASE STUDY SETUPS AND DATA ACQUISITION

Two experiments were carried out at the campus of the National Technical University of Athens (NTUA) in which two driving scenarios were implemented in mixed (outdoor–indoor) environments. At the data preanalysis 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. Although the core objective of this research relates to indoor spaces, these experiments were operated in a mixed indoor–outdoor environment. The main reason for this operation is that GNSS coverage was exploited to visualize the data (e.g., trajectories) and verify the accuracy of the opportunistic sensors (e.g., smartphone sensors) against the higher-accuracy equipment. Another reason is that the environments of interest sometimes offer partial GNSS coverage (e.g., access to parking facilities or depots, or open areas in a predominantly covered facility). In any case, specific care was given to ensure that no information that would otherwise not be available in an indoor environment was 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 with different drivers. Because of space restrictions, the setup of the two experiments is presented in parallel next, and some aspects are not fully described.

Experiment NTUA-1

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 on March 27, 2014; a total distance of about 2.5 km for a time span of 12 min was driven. The traveled path included a small indoor parking facility and segments with open spaces (Figure 1*a*). Data acquisition was performed by using two contemporary smartphone units: an Apple iPhone 5 and an HTC One S. Also, a NovAtel SPAN system consisting of a geodetic-grade GNSS receiver (NovAtel ProPak-V3) and a tactical-grade inertial measurement unit (IMU) (iMAR IMU-FSAS) was employed to



(a) (b) (c)

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

provide the vehicle's reference trajectory. The latter offers a nominal RMS acceleration accuracy of ±0.03 m/s^2.

The driving speed range was constrained to normal city driving speeds, whereas higher acceleration and deceleration values were pursued in straight segments. All sensors were collocated, aligned to the vehicle body frame, and fixed onboard on a purpose-built platform on the vehicle roof. Sensor location is illustrated in Figure 1*c*; the XSENS system (situated in the top left of Figure 1*c*) 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 with third-party software (mobile applications); 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 10 Hz and 65 Hz, respectively. The events and scenarios simulated along the traveled path are documented in Table 2.

Experiment NTUA-2

The second experiment, NTUA-2 (Figure 1*b*), took place on June 12, 2014. This experiment aimed both at collecting a relatively larger data set and 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 upward and downward. Furthermore, the test vehicle traveled for

TABLE 2 Event Documentation for Field Tests: Events of Interest During Experiment NTUA-1

Event Type (NTUA-1)	Start Time (h:min:s)	End Time (h:min:s)	Duration (h:min: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

TABLE 3 Event Documentation for Field Tests: Events of Interest During Experiment NTUA-2

Event Type (NTUA-2)	Start Time (h:min:s)	End Time (h:min:s)	Duration (h:min: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	na[a]	na[a]
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	na[a]	na[a]
Alignment (acceleration and 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	na[a]	na[a]
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

NOTE: na = not applicable.
[a]Instantaneous event for which end time and duration do not make sense.

relatively long periods in closed spaces to realize the indoor environment. Data were acquired by driving a total distance of approximately 4.4 km spanning a time period of 20 min.

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 of 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 by using the SensorLog software operating at 10 Hz. The events of specific interest were logged manually and are outlined in Table 3.

ASSESSMENT OF NAVIGATION SOLUTION

Raw data acquisition from smartphone navigation sensors of variant characteristics is not a trivial task because data sets 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., processor, random-access memory, 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 in 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. Therefore, data resampling and synchronization were addressed before data analysis. Initially, all sensor records were resampled to 10 Hz, the lowest sampling rate among the sensors used. To achieve sensor synchronization and mitigate potential drifts, all data sets were cross-compared with the reference data set obtained by using the NovAtel SPAN system.

Navigation Data Assessment

For the NTUA-1 experiment, the standardized data set comprises 7,311 records per sensor corresponding to a time span of 12 min (15:01:30 to 15:13:41). Table 4 shows the acceleration statistics computed for all recording devices. Clearly, there is relatively good agreement among all units. However, a significant difference (132%) was observed in the standard deviation obtained for the HTC One S (±1.35 m/s^2) and the SPAN system (±0.58 m/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 and contributed to a higher standard deviation value. In effect, it appears that z-acc takes a near-zero value instantly that immediately afterward drops to its normal level. This bias is unique to the HTC One S smartphone and is attributed to data collection software issues; the finding suggests that data acquisition software can be critical for further analysis. This issue was resolved for the subsequent experiments, including NTUA-2.

For NTUA-2, a total of 11,951 epochs of data per sensor were processed, spanning a time period of 20 min (18:16:50 to 18:36:45). Table 5 shows the acceleration statistics obtained for all sensors. As in the NTUA-1 experiment, the test smartphone devices generally agree with the SPAN system. Besides, the HTC One S shows a more consistent logging behavior compared with the previous experiment; this behavior is attributed to the change of data acquisition software (i.e., SensorLog from IMU+GPS-Stream). Of note

TABLE 4 Statistics of Collected Data: Accelerations for NTUA-1

	x-acc (m/s^2)				y-acc (m/s^2)				z-acc (m/s^2)			
Device	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

NOTE: Acc = acceleration; min. = minimum; max. = maximum.

TABLE 5 Statistics of Collected Data: Accelerations for NTUA-2

	x-acc (m/s^2)				*y*-acc (m/s^2)				*z*-acc (m/s^2)			
Sensor	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

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 finding is potentially due to the ability of XSENS to log readings for a wider acceleration range (±15 *g*) compared with other sensors (up to ±5 *g*). A noticeable difference (26%) can also be seen for *x*-acc.

Table 6 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 those of other units and result in a significant difference from SPAN in the mean *x*- and *z*-gyro values. Interestingly, no significant differences are observed in the corresponding standard deviations and maximum or minimum values; this finding suggests a bias in the iPhone measurements the source of which remains undetected.

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). Visible changes of acceleration values of an abrupt character are noted for all recording devices and for all four speed hump locations. Notably, the excessive noise in the SPAN data is due to unsmoothed observables.

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

DRIVER BEHAVIOR CLASSIFICATION ANALYSIS

For 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, a number of indexes were considered 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 indexes. Internal indexes provide insight supporting the choice of the optimal number of clusters. In contrast, external indexes 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 the 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 indexes considered. Although 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 data sets 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, whereas the decision rule "max diff" corresponds to the greatest difference between two successive slopes, that is, to the elbow in the curve.

External indexes were then applied to the data series in order to compare the clustering results between three and five clusters

TABLE 6 Statistics of Collected Data: Angular Velocity Data for NTUA-2 Test

	x-Gyro (°/s)				*y*-Gyro (°/s)				*z*-Gyro (°/s)			
Device	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

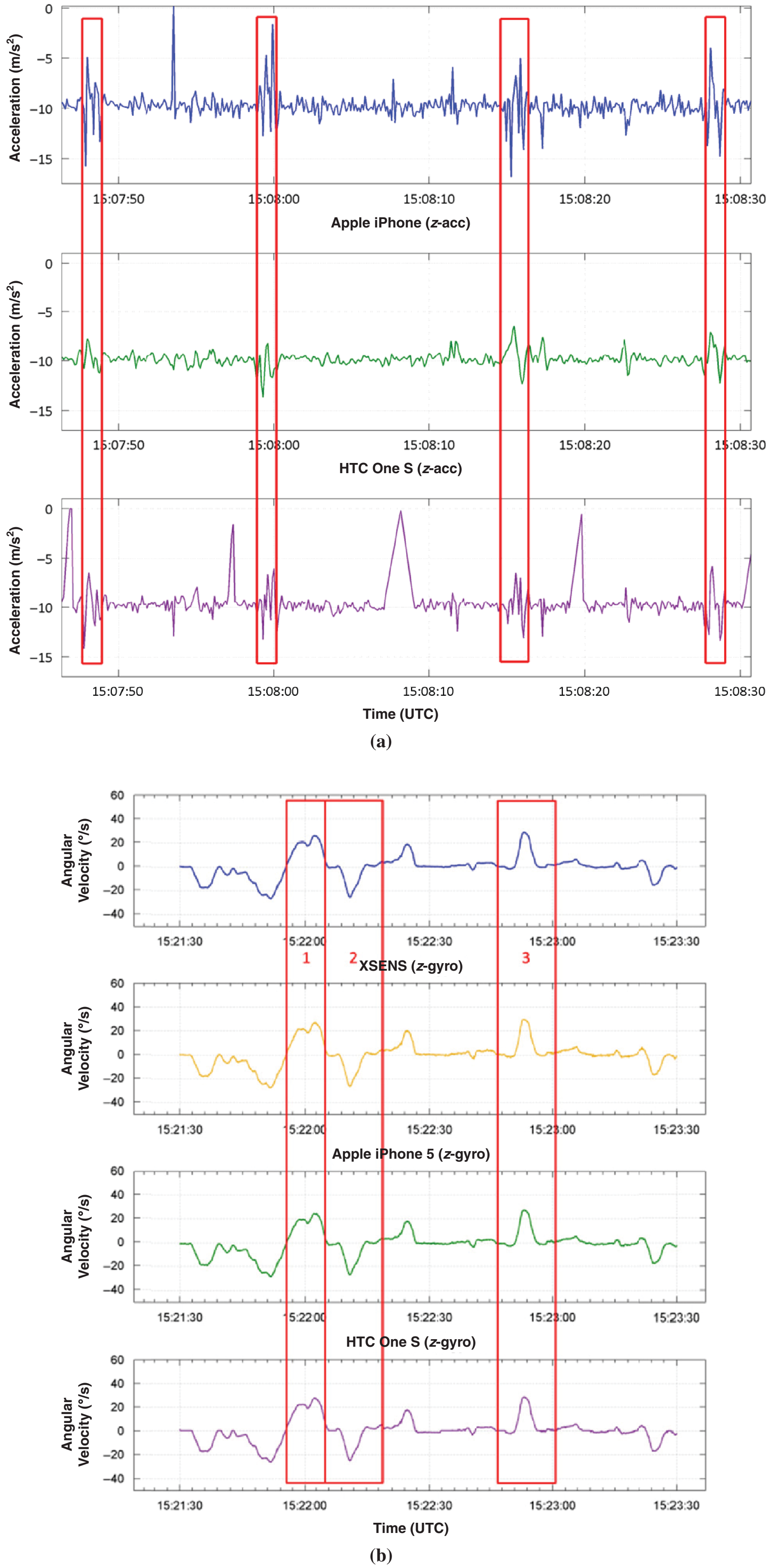


FIGURE 2 Interpretation of sensor data: (*a*) NTUA-1, speed hump detection example based on *z*-acc measurements (spikes for HTC One S due to logging issue and resolved for NTUA-2), and (*b*) NTUA-2, smartphone *z*-gyro sensor readings for subset of NTUA-2 test (UTC = coordinated universal time).

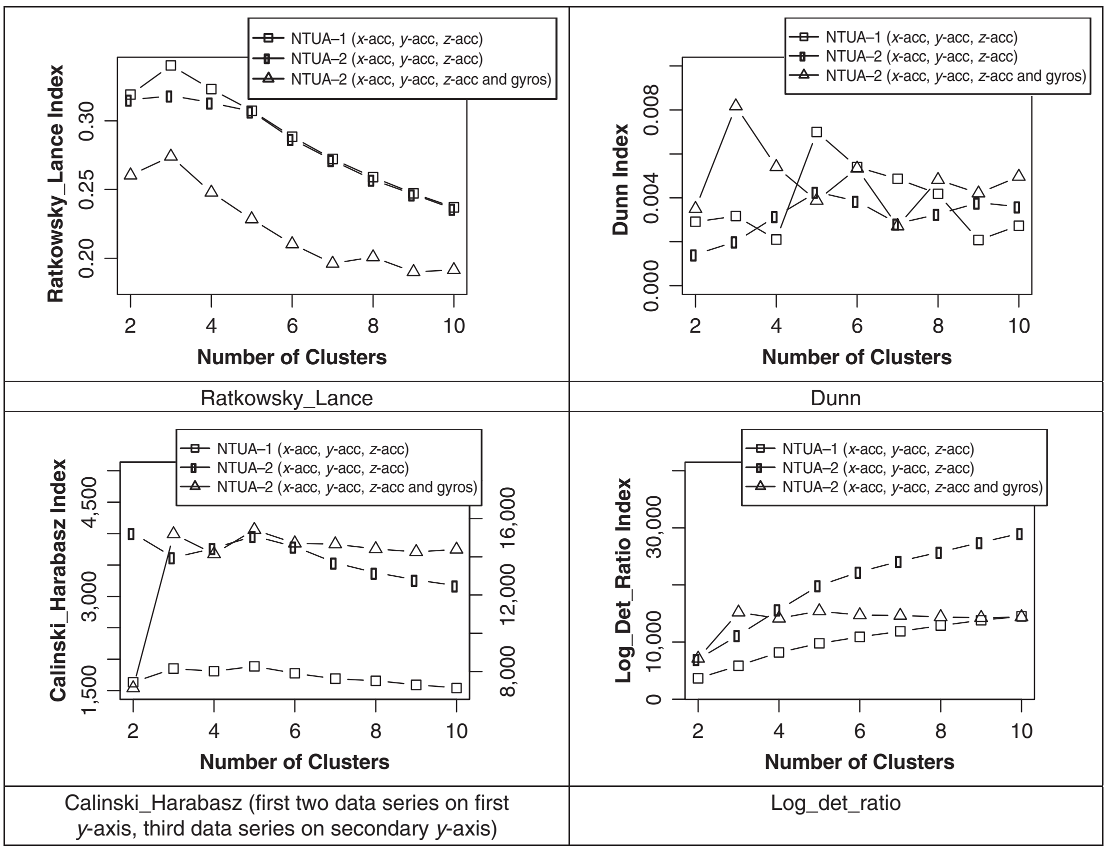
Internal Index	Optimal Number of Clusters		
	NTUA-1	NTUA-2 (no gyros)	NTUA-2
Ratkowsky_Lance (rule: max.)	3	3	3
Dunn (rule: max.)	5	5	3
Calinski_Harabasz (rule: max.)	5*	2*	5 / 3
Log_det_ratio (rule: max. diff.)	4	5	3

*not sensitive

(a)

	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)



(c)

FIGURE 3 Internal and external indexes for determination of optimal number of clusters: (*a*) choice of optimal number of clusters according to internal indexes (* = not sensitive), (*b*) comparison of partitions (three and five clusters), and (*c*) visual presentation of sensitivity of internal indexes to number of clusters.

(Table 5). The general concept is that the indexes measure the degree to which points move across clusters as the number of clusters increases. For instance, the Fowlkes–Mallows index could be evaluated on the basis of the number of points that are common or uncommon in the two hierarchical clustering options. It may be concluded that for NTUA-2, and especially for the richer information case including gyros, the clustering between three and five clusters seems to be more similar. This finding could be explained by the fact that more data may allow a more accurate clustering, even with three clusters.

In order to develop deeper insight into the clustering results, clustering results for three and five clusters are presented in Figure 4.

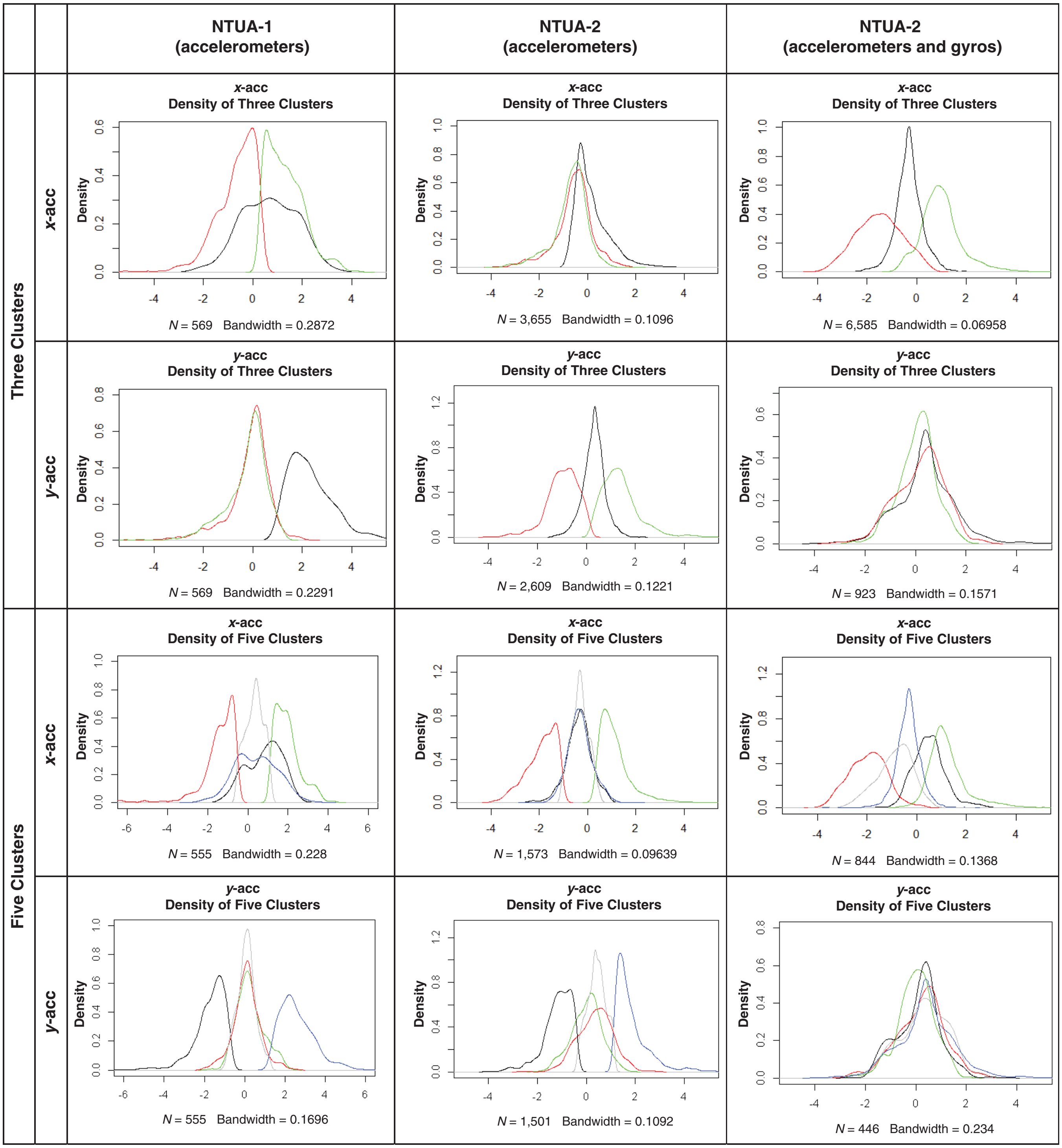


FIGURE 4 Clustering results for three and five clusters.

The z-axis accelerations are not presented since 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 five clusters is crisper than with three clusters, and
- NTUA-2 results in a better clustering in y-acc because NTUA-1 includes essentially only left turns.

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. Although some aspects can be assumed to be at a level in which 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 is still a challenging endeavor. Similarly, modeling low-speed traffic is also a challenging task (often leading to underestimation of the capacity), whereas parking maneuvers and their impact on the following and opposing vehicles are aspects in which modeling can be improved [see, e.g., work by Kladeftiras and Antoniou (*29*)].

Simulation of indoor environments, such as those considered in this research, requires challenging aspects of modeling vehicle operations at a microscopic scale in parking facilities; this modeling combines a number of restrictions along the state of the art of traffic modeling and simulation: complex geometry, congested conditions, and very low speeds. It is possible that models of gap acceptance and merging that are formulated or estimated for general traffic will perform poorly when applied to modeling traffic facilities. Flexible, data-driven models 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 (*30, 31*).

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

The absence of direct GNSS coverage in these applications means that innovative approaches may be employed to the localization of vehicles. 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 in localization of vehicles; furthermore, low speeds within the facilities of interest in this research reduce the complexity of the problem.

Finally, in this research the focus is on smartphone sensors; exploitation of 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 a prerequisite for the design of a successful positioning application is the identification of an optimal trade-off between reliability and complexity. Many practical challenges need to be addressed by industry and academia in this field. Some of them are as follows:

- Mobile terminal–related measurements. There is heterogeneity of the wireless cards of mobile terminals and consequently there are differences in the estimated values of the received signal strength and biases in the whole procedure of indoor positioning.
- Wireless link–related measurements. The time-varying nature of the wireless channel is introduced as a result of the motion of the vehicles, the humans, the fact that the mobile terminal is inside the vehicle, and other aspects. Another problem is the channel dispersion of the signal 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 (2.4 GHz, 5.2 GHz, 5.8 GHz, 28 GHz, 60 GHz, etc.) that confront different propagation phenomena.
- Optimum placement of the access points. Optimum placement strongly depends on the indoor environment, the building materials, the number of vehicles, the walls, the floors, and other factors. It is important to optimize the coverage and the connectivity of the access points.
- Usage of multiple antennas and multinode technologies. Large-scale multiple-input and multiple-output techniques would increase the accuracy of the indoor positioning system. However, their deployment in the current systems would also increase the complexity.

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