Smartphones as an integrated platform for monitoring driver behaviour: The role of sensor fusion and connectivity

Kanarachos, S., Christopoulos, S. & Chroneos, A.

Original citation & hyperlink:
Kanarachos, S, Christopoulos, S & Chroneos, A 2018, 'Smartphones as an integrated platform for monitoring driver behaviour: The role of sensor fusion and connectivity', Transportation Research Part C: Emerging Technologies, vol. 95, pp. 867-882.
https://dx.doi.org/10.1016/j.trc.2018.03.023

DOI 10.1016/j.trc.2018.03.023
ISSN 0968-090X
ESSN 1879-2359

Publisher: Elsevier

Smartphones as an integrated platform for monitoring driver behaviour: The role of sensor fusion and connectivity

Stratis Kanarachos,[1] Stavros-Richard G. Christopoulos[1,2] and Alexander Chroneos[1]

[1]*Faculty of Engineering, Environment and Computing, Coventry University, Priory Street, Coventry CV1 5FB, United Kingdom*

[2]*Solid Earth Physics Institute, Faculty of Physics, National and Kapodistrian University of Athens, Panepistimiopolis, Zografos 157 84, Athens, Greece*

Corresponding author: Stratis Kanarachos, stratis.kanarachos@coventry.ac.uk, Faculty of Engineering, Environment and Computing, Coventry University, Priory Street, Coventry CV1 5FB, United Kingdom

Abstract

Nowadays, more than half of the world's web traffic comes from mobile phones, and by 2020 approximately 70 percent of the world's population will be using smartphones. The unprecedented market penetration of smartphones combined with the connectivity and embedded sensing capability of smartphones is an enabler for the large-scale deployment of Intelligent Transportation Systems (ITS). On the downside, smartphones have inherent limitations such as relatively limited energy capacity, processing power, and accuracy. These shortcomings may potentially limit their role as an integrated platform for monitoring driver behaviour in the context of ITS. This study examines this hypothesis by reviewing recent scientific contributions. The Cybernetics theoretical framework was employed to allow a systematic comparison. First, only a few studies consider the smartphone as an integrated platform. Second, a lack of consistency between the approaches and metrics used in the literature is noted. Last but not least, areas such as fusion of heterogeneous information sources, Deep Learning and sparse crowd-sensing are identified as relatively unexplored, and future research in these directions is suggested.

Keywords

Smartphones; driver behaviour; sensor fusion; connectivity; cybernetics; crowd-sensing;

Introduction

Nowadays, the use of smartphones is, indisputably, a part of our lives. The fact that everything is becoming more portable is among others a result of this interaction (Shuib et al., 2015). In the late 1990s and within a few years the use of mobile phones completely changed the way of communication both in social and professional level (Comer and Wikle, 2008). A few years later, mobile Internet technology enabled us to exchange data, emails and mobile browsing giving us access to more information in our everyday life. Fast mobile Internet in combination with more advanced smartphone operating systems (i.e. Android, iOS) generated further opportunities for applications in multimedia, cloud-based services and mobility (Khan et al., 2013). At the end of the 2010s, the embedment of sensors facilitated the use of smartphones as flexible mobile measurement devices, see Table 1 (Ganti et al., 2011). Furthermore, from 2014 onwards, the operating system of smartphones improved significantly bringing energy savings and enhanced connectivity, see Table 2. Different fields of research investigated the new sensing and communication capabilities, including health monitoring (Ben-Zeev et al., 2015), commerce (Shaikh and Karjaluoto, 2015), education (Merchant, 2012), and well-being (Morillo et al., 2015).

Table 1: Embedded sensors in a modern smartphone per Android version. In brackets the release date of the Android platform.

Sensor	**Android 1.5** [04/2009]	**Android 2.3** [12/2010]	**Android 4.0** [10/2011]	**Android 4.3** [7/2012]	**Android 5.0** [11/2014]	**Android 6.0** [10/2015]	**Android 7.0** [08/2016]
Temperature	☺	☺	☺	☺	☺	☺	☺
Camera	☺	☺	☺	☺	☺	☺	☺
GPS	☺	☺	☺	☺	☺	☺	☺
Microphone	☺	☺	☺	☺	☺	☺	☺
Accelerometer	☺	☺	☺	☺	☺	☺	☺
Ambient temperature	–	–	☺	☺	☺	☺	☺
Gravity	–	☺	☺	☺	☺	☺	☺
Gyroscope	–	☺	☺	☺	☺	☺	☺
Light	☺	☺	☺	☺	☺	☺	☺
Linear acceleration	–	☺	☺	☺	☺	☺	☺
Orientation	☺	☺	☺	☺	☺	☺	☺

Pressure	–	☺	☺	☺	☺	☺	☺
Proximity	☺	☺	☺	☺	☺	☺	☺
Relative humidity	–	–	☺	☺	☺	☺	☺
Rotation vector	–	☺	☺	☺	☺	☺	☺
Game rotation vector	–	–	–	☺	☺	☺	☺
Tilt detector	–	–	–	–	☺	☺	☺
Gesture sensor	–	–	–	–	☺	☺	☺

Table 2: Operating system changes per Android version. In brackets the release date of the Android platform.

	Communication	**Battery management**
Android 5.0 [11/2014]	• New multi-networking features allow apps to query available networks such as Wi-Fi and cellular.	• Allows apps to perform concurrent operations with Bluetooth Low Energy (BLE), allowing both scanning and advertising.
Android 6.0 [10/2015]	• Allows association of an app with a web domain. • Allows users to directly share content. • Allows voice interaction	
Android 7.0 [08/2016]		• Improved battery life by deferring CPU and network activities when device is unplugged, stationary, and with the screen turned off. • Removal of implicit broadcasts and therefore unnecessary apps operation.

This survey focuses on the use of smartphones as integrated platforms for monitoring driver behaviour, specifically the strategic and manoeuvring levels (Michon, 1985). The strategic and manoeuvring levels are interrelated and useful for the evaluation of Intelligent Transportation Systems (Chong et al., 2013). The driver behaviour at the reactive level was omitted, as it refers to actions with a span of only a few milliseconds. Modern cars have much more powerful computing capacity on board compared to smartphones for real-time and safety-critical applications[1]. The theoretical framework of this review is the Cybernetics model, (Simpkins and Simpkins, 2012), see

[1] https://www.engadget.com/2018/01/07/nvidia-xavier-soc-self-driving-cars/, accessed on 10/03/2018

Fig. 1. According to Cybernetics, driver behaviour depends on the iterative execution of a loop comprising five elements: sensing, information processing, decision-making, feedback and action.

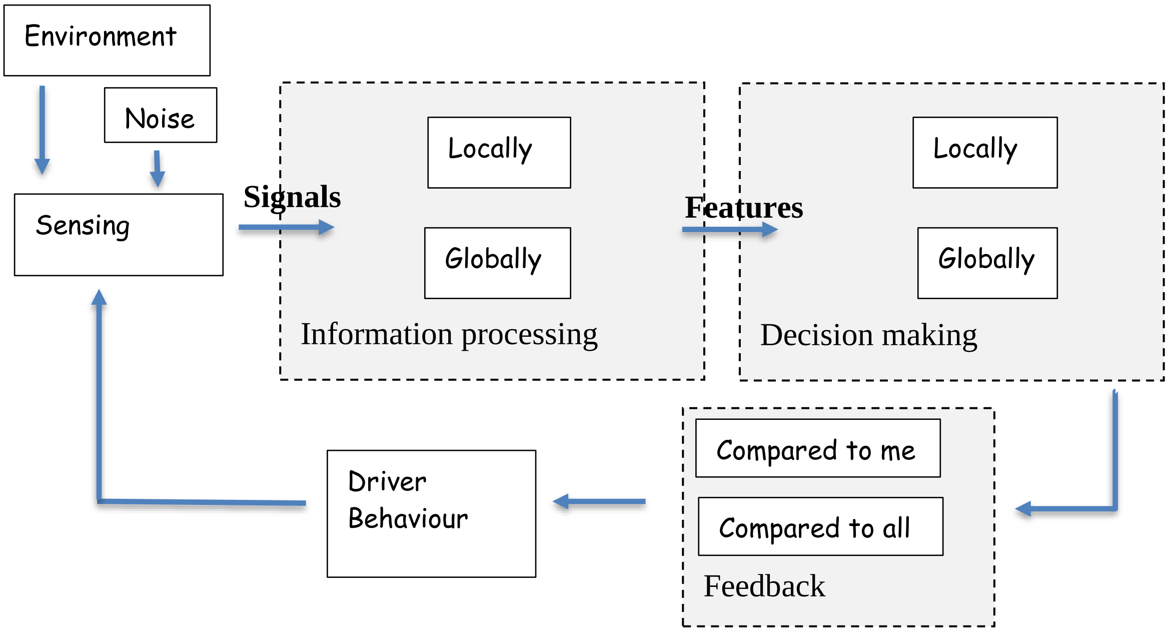


Fig. 1: Cybernetics paradigm: Driver behaviour depends on the iterative execution of sensing, information processing, decision-making, feedback and action.

The survey mainly considered scientific contributions that were comprehensive and self-contained, to allow theoretical comparison. We used the Scopus online database for this purpose. The survey did not cover non-smartphone-based publications. Driver behaviour was considered in a multi-modal context; for example, it is of interest to know the transportation mean used by the driver for the last mile coverage (park and ride schemes). Fig. 2 depicts a schematic of the review.

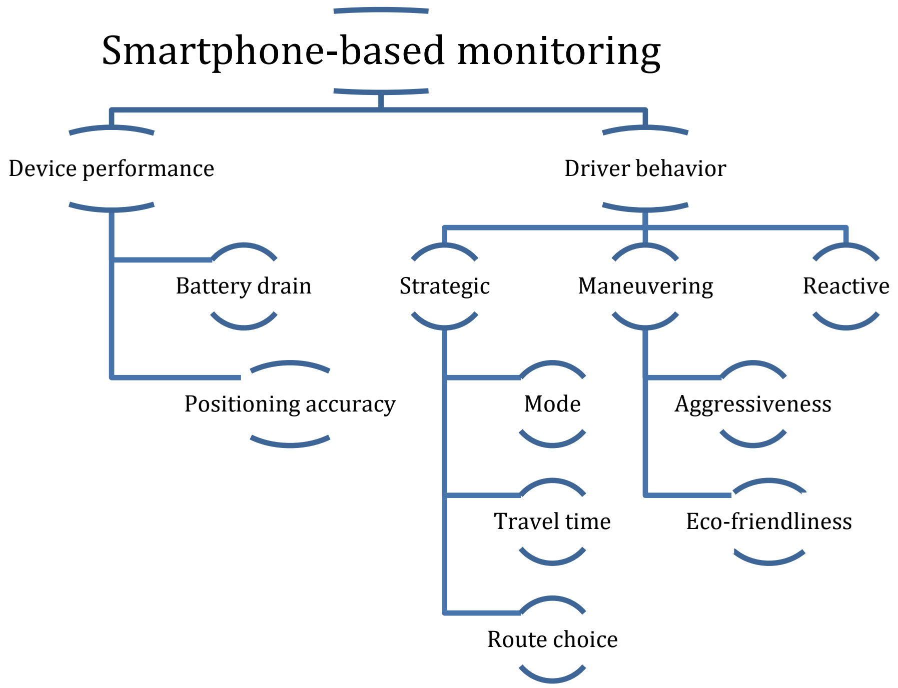


Fig. 2: Conceptual scheme of the review. A survey on smartphone-based methods for integrated monitoring of driver behaviour.

Smartphones have several shortcomings that may pose limitations to their use as integrated platforms. First, the low accuracy of smartphone signals, as smartphone sensors are usually from the lowest commercial grade. Second, the need to drain as little battery energy as possible. Although it is possible to charge the smartphone inside the vehicle, the drivers may use different transportation means in their journey. Third, the limited processing power compared to the one available on board of a vehicle. The latter was one of the main reasons why reactive driver behaviour was not covered. On-board vehicle systems are more suitable for this. On the other hand, smartphones facilitate crowd sensing, not possible for the majority of the current vehicle fleet. Hence, the research questions that drove this survey are: a) How was information fused and what was the role of connectivity? b) Which are the best practices that overcome smartphone shortcomings?

The paper is organised into five sections: Section 2 discusses sensor fusion methods for improving smartphone positioning accuracy and reducing battery drain. Smartphone-based driver behaviour monitoring at the strategic and manoeuvring levels is the focus of Section 3. In Section 4, a critical analysis of the publications reviewed is given. The conclusions and future research directions are given in Section 5.

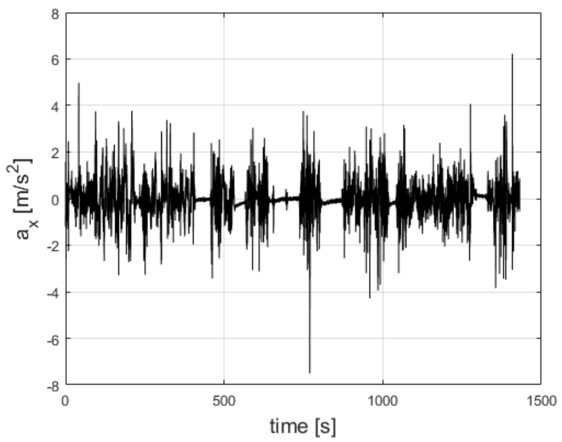
2 Smartphone-based vehicle positioning

Smartphone-based vehicle positioning solutions upturned around 2008 when GPS antennas and navigation maps commenced in smartphones. Smartphone-based positioning suffers mainly from relatively low positioning accuracy and high battery drain (Menard *et al*., 2011a, Menard *et al*., 2011b, Chowdhury *et al*., 2016, Humphreys *et al*., 2016;).

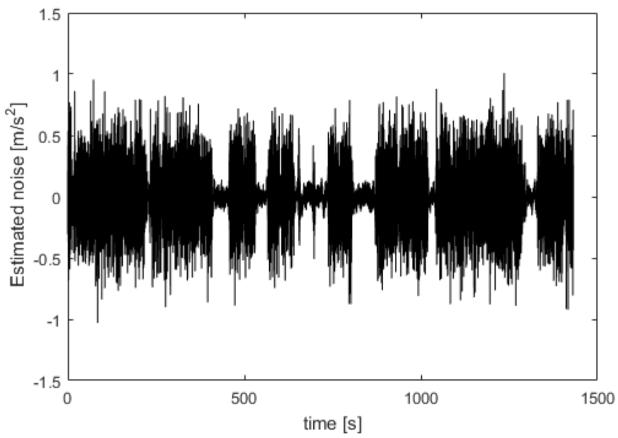
2.1 Battery drain reduction

Smartphones can achieve long battery autonomy by frequently entering and exiting the so-called "sleep" mode. During GPS operation smartphones cannot enter the sleep mode, and significant amounts of energy are consumed. This happens because they communicate for an extended period with some satellites and perform computationally intensive calculations to determine the vehicle position. Different solutions have been proposed to reduce GPS usage and therefore energy consumption. From a sensor fusion point of view, three main approaches were identified, and typical examples are summarised in Table 3. The first approach combines the accelerometer and GPS speed signals to infer vehicle motion. During standstill the acceleration and the respective noise level are considerably smaller. The energy consuming GPS signal is requested only when the vehicle is moving (Lin et al., 2014; Oshin et al., 2012).

Fig. 3 illustrates the longitudinal acceleration and its noise level of a vehicle, measured using a smartphone, during a naturalistic driving field trial in Coventry, U.K. (Christopoulos, *et al*., 2018). As observed the periods at which the vehicle is not moving are relatively small. However, during traffic congestion, the proportion can become more substantial. The second approach combines cellular, Wi-Fi networks, and GPS (Anagnostopoulos et al., 2016; Bareth and Kupper, 2011). The coordination is performed hierarchically, based on the energy efficiency and positioning accuracy of each technology. The relative energy efficiency and positioning accuracy of each technology is reported in the review study by Wahlström *et al*. (2017). The particular solution depends on the available infrastructure, for example, Wi-Fi has much lower accuracy in rural compared to urban areas. The third approach reduces battery drain by transferring the computationally intensive calculations from the smartphone to the cloud (Liu et al., 2016). Prerequisite for this type of solution is the reliable and continuous communication between the smartphone and the server.



a)



b)

Fig. 3: a) Vehicle longitudinal acceleration measured using a smartphone during a naturalistic drive in Coventry city, U.K. b) Estimated noise level in the acceleration signal using wavelet decomposition (Christopoulos, et al., 2018).

Table 3 lists the energy savings reported in the publications reviewed. The energy savings refer to the reduction of smartphone battery drain. The experiments were not standardised, so a direct comparison was not possible. Differences in the values reported should be expected if the experiments were repeated in an environment with different infrastructure. In any case, it is still possible to appreciate the order of magnitude of the potential energy savings. The hierarchical approach reports the best results. This outcome is very encouraging as with the proliferation of 5G networks, performance and energy savings will further improve. On the other hand, this solution can be implemented only in particular geographic areas. For example, 5G network coverage is expected only in urban areas[2]. Considerable energy savings were reported also with mobile cloud computing. There, the GPS computationally and energy-intensive calculations are performed in the cloud. Mobile cloud computing is dependent on the mobile network capacity and available bandwidth (Akherfi *et al.*, 2018). The lowest reported energy saving potential was achieved when the smartphone signals were fused locally. The energy savings were approximately 25%, which is still a considerable amount.

Table 3: Comparison of smartphone battery energy savings using different sensor fusion methods

Reference	**Short description**	**Sensors**	**Energy savings**
Oshin *et al.*, 2012	GPS signal acquired only when vehicle is moving	GPS, accelerometer	27.0%
Lin *et al.*, 2014	Accelerometer-based positioning. Absolute position correction at frequent intervals using GPS signals and map information.	GPS, accelerometer, compass, Navigation maps	24.7%
Bareth and Kupper, 2011, Anagnostopoulos *et al.* 2016	Hierarchical approach utilizing either the cellular network, WiFi network or GPS.	Cell-ID, WiFi, GPS	90.0%
Liu *et al.*, 2016	Energy consuming calculations are performed on the cloud	GPS	66.6%

2.2 Positioning accuracy improvement

GPS positioning accuracy is a function of GPS signal quality, which depends on several factors including the number of visible satellites, weather and surroundings such as buildings and trees. The latter is also known as the urban canyon effect (Groves, 2011; Wang et al., 2012; L. Wang et al., 2013). Fig. 4 shows the typical accuracy of the smartphone GPS position signal during a naturalistic driving field trial in the area of Coventry, U.K. (Christopoulos et al., 2018). Positioning accuracy is on average 3 m, however, degrades significantly in some areas, depending on the situation. Two use cases dominate the literature on smartphone-based vehicle positioning. The first aims to maintain positioning accuracy when the GPS signal is weak or lost. The second is focused on achieving lane level accurate positioning.

[2] https://5g.co.uk/coverage/, accessed on 10/03/2018

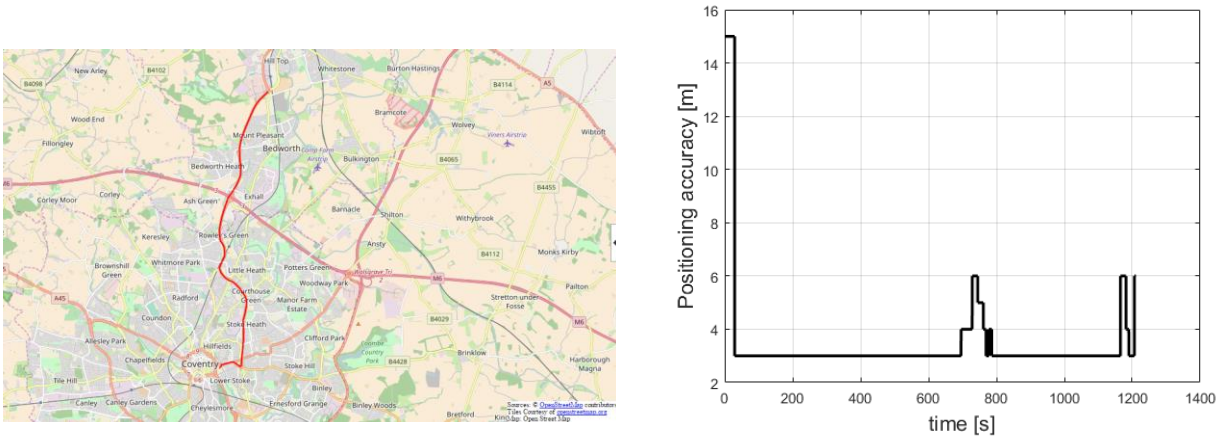


Fig. 4: a) Route followed during a naturalistic driving field trial in the U.K. (indicated with red colour) b) Corresponding smartphone GPS positioning accuracy. Degradation while crossing bridges and entering the urban area (Christopoulos, et al., 2018).

Table 4 summarises the performance of the different sensor fusion methods. The Input Delay Neural Network (IDNN) method achieves better positioning accuracy compared to the Radial Basis Neural Networks and Kalman Filter (Noureldin et al., 2011). Table 5 provides details of the comparison between them. Notably, the performance of Kalman Filter is worse for more extended GPS outages. Input Delay Neural Networks have a higher dependency on past sampling instants than Radial Basis Neural Networks and Kalman Filter. The average positioning error using IDNN was 2.7 m in the Longitude and 3.8 m in the Latitude. It is noted that the accuracy using IDNN was better than the one in Zirari et al. (2010), where a hierarchical approach combining cellular, WiFi and GPS positioning was used. It was also better than the one in Wang et al. (2012), where a virtual model of the city was employed to compensate the effects of the urban canyon on GPS signal quality.

On the other hand, the level of accuracy using Input Delay Neural Networks is not that of lane level. The latter seems to be feasible only when cameras and maps that include lane information are employed. As a means to reduce battery drain, Dabove *et al*.(2015) and Song *et al*. (2014) explored the possibility to achieve lane-level accuracy by intermittently using the camera. A potential way to improve GPS position accuracy is by sharing the GPS information between smartphone road users and other infrastructure objects of known GPS location. Unfortunately, this idea has been studied only in simulation or using DSRC (Dedicated Short-Range Communications) vehicle to vehicle communication (Bento et al., 2017; Espada et al., 2014).

Table 4: Comparison of smartphone-based positioning accuracy using different sensor fusion methods

Reference	**Short description**	**Sensors**	**Accuracy**
Zandbergen, 2009	Switch between Cell-ID, WiFi and GPS	GPS, Wi-Fi, Cell-ID	• GPS: Median error value 8 m • WiFi: Median error value 74 m • Cell-ID: Median error value 600 m
Zirari et al., 2010	WiFi position when GPS signal is weak or lost	GPS, WiFi	Maximum positioning error below 100 m
Noureldin *et al.*, 2011	Input Delayed Neural Networks to estimate the speed and position of the vehicle during GPS outage	GPS, accelerometer, gyroscope	For a GPS outage 100s: • Average positioning error - Longitude: 2.7 m • Average positioning error - Latitude: 3.8 m • Maximum positioning error: 7.9 m
	Radial Basis Function Neural Networks to estimate the vehicle position during GPS outage	GPS, accelerometer, gyroscope	GPS outage 100s • Average positioning error - Longitude: 4.7 m • Average positioning error - Latitude: 7.1 m • Maximum positioning error: 12 m
	Kalman filter to estimate the vehicle position during GPS outage	GPS, accelerometer, gyroscope	GPS outage 100s • Average positioning error - Longitude: 6.8 m • Average positioning error - Latitude: 8.5 m • Maximum positioning error: 18 m
Bierlaire *et al.*, 2013	Probabilistic method for fusing GPS data and map trajectories	GPS	Not reported
Guido *et al.*, 2014	Probabilistic method for estimating speed confidence intervals in relation to signal strength	GPS	Speed intervals as a function of GPS signal quality
Song *et al*, 2014	- Camera to identify the lane in which the vehicle is driving. - Inertial Measurement Unit to identify the lane changes.	accelerometer, gyroscope, camera, map	88.5% accurate in detecting the correct lane (maximum positioning error ≈ 1.5 m)
Espada *et al.*, 2014	- Nearby smartphones share GPS position. - Smartphone with best GPS position accuracy is used as a reference.	GPS, Wi-Fi direct	Not reported
Dabove *et al.*, 2015	- Inertial Measurement Unit to provide the relative position of the vehicle. - Camera to capture the position of the vehicle in relation to the environment (eliminate drift using map information).	accelerometer, gyroscope, camera	• Maximum positioning error: 0.5 m for an update frequency 2 s • Maximum positioning error: 2.2 m for an update frequency 5 s
Wang *et al.*, 2012, Wang *et al.*, 2015	City buildings 3D virtual model estimates signal strength and multipath error at different positions	GPS	Average cross-street positioning error below 5 m

Aly *et al.*, 2016	- Lane and lane changes detection using lateral accelerometer and map information - Detection of lane anchors using accelerometers and crowdsourcing	Accelerometer, camera	Accurate detection of lane position 84% of the time

Table 5: Positioning error during GPS outage using Input Delay Neural Networks (IDNN), Radial Basis Function Neural Networks (RBFNN) and Kalman Filter (KF) (Noureldin et al., 2011)

		Positioning error [m]		
GPS outage		IDNN	RBFNN	KF
40 s	Longitude	1.8	2.5	1.9
	Latitude	3.8	3.5	3.6
100 s	Longitude	2.7	4.7	6.8
	Latitude	3.8	7.1	8.6

3 Smartphone-based monitoring of driver behaviour

Driver behaviour can be distinguished in three levels depending on its time scale: strategic, tactical and reactive. The strategic defines the general planning stage of a trip including the determination of trip targets, route selection, and transportation mode choice (Michon, 1985). The time scale at this level is the longest one and decisions may influence driver behaviour for a period of a few minutes up to several hours.

3.1 Transportation mode classification

Smartphone-based transportation mode classification has attracted the interest of academia and industry. Table 6 compares relevant scientific contributions. The comparison is based on the Cybernetics model. In this context, the signals, decision-making method, sensor fusion level, noise rejection, feedback level, and performance are reported. The symbol “LS” refers to sensor fusion at the smartphone, while “CS” refers to uploading the raw data to a server and then combining the signals centrally. In case the method provides a probabilistic formulation (one that can be tuned) for rejecting noise and outliers embedded in the signal the check symbol "✓" is used. In the opposite case we use the dash symbol "–". Feedback is distinguished between "Compared to me" and "Compared to all". We choose the first option when driver behaviour is evaluated only based on its performance. The latter is used when the driver behaviour is compared to others performance. The metrics used in different studies in general vary.

A crowd-sensing method employing Support Vector Machines reported the best performance, 99% classification accuracy (Semanjski and Gautama, 2016). Several parameters were fused to perform the classification including the GPS position, duration of the trip, distance covered, user i.d. and time of the day. When signals were combined only at the smartphone level, the best performance was 97% (Martin et al., 2017). Only speed and acceleration were fused in that case.

Some studies suggest that the acceleration signal is not that informative because a similar range of values is obtained for a variety of transportation modes (Biljecki et al., 2013). Because of this the classification of specific transportation modes, for example that of a bicycle, is particularly difficult. A variety of rule based and probabilistic methods were developed to compensate for the ambiguity in the data (Eftekhari and Ghatee, 2016; Xiao et al., 2015, Martin et al., 2018). Bayesian networks, random forests and fuzzy expert systems were among those reviewed.

Table 6: Comparison of sensor fusion methods for smartphone-based classification of transportation mode

Transportation mode classification	**Signals**	**Method**	**Fusion**	**Noise**	**Feedback**	**Performance**
Byon et al., 2009	Speed, acceleration, number of satellites, Horizontal Dilution of Precision	Neural Networks	LS	–	Compared to me	60-98%
Xiao *et al.*, 2012/	Speed, acceleration	Rule based	LS	–	Compared to me	n/a
Biljecki *et al.*, 2013	Speed, map information	Fuzzy expert	LS	✓	Compared to me	92% accuracy

Feng and Timmermans, 2013	Speed, acceleration	Bayesian Network	LS	✓	Compared to me	92%
Byon and Liang, 2014	Speed, acceleration, number of satellites in view, magnetometer	Neural Networks	LS	−	Compared to me	74-83%
Xiao *et al*. 2015	Speed, acceleration, travel distance	Bayesian Network	LS	✓	Compared to me	93-95%
Assemi *et al*., 2016	Speed, acceleration, orientation, distance	Multinomial Logistic Regression Model	LS	−	Compared to me	95%
Eftekhari and Ghatee, 2016	Speed, acceleration, orientation	Rule based	LS	−	Compared to me	95%
Semanjski and Gautama, 2016	User ID, duration, distance, transportation mode, start and end time, GPS position	Support Vector Machines	CS	−	Compared to all	99%
Martin et al., 2018	GPS position, accelerometer	Movelets, k-nearest neighbors, feature extraction	CS	−	Compared to me	89%
	GPS position, accelerometer	Movelets, random forests, feature extraction	CS	✓	Compared to me	97%
Dabiri and Heaslip, 2018	GPS position	Outlier removal, Convolutional Neural Networks	CS	−	Compared to me	85%

S: Smartphone based fusion
CS: Crowd sensing based fusion
Noise: The method provides a probabilistic framework for rejecting noise and outliers contained in the signal
Compared to me: Feedback is provided to the driver using absolute metrics
Compared to all: Feedback is provided to the driver using relative metrics (compared to peers or drivers using the same routes)

For the classification task several machine learning approaches have been tried out. It was not possible to derive general conclusions by directly comparing the results of the different studies because details on the implementation, tuning and data used for the training task were usually not reported. However, it was possible to derive conclusions based on some comprehensive papers. In Xiao et al. (2015) Bayesian Networks performed better than Support Vector Machines (SVM) and SVMs better than Neural Networks. Table 7 lists the performance achieved for the training and test sets separately. The latter is a measure of the generalisation capability of the method. Bayesian Networks outperformed SVMs by 2.5% in the training set and 7% in the test set. In Eftekhari and Ghatee (Eftekhari and Ghatee, 2016) Neural Networks, k-Nearest Neighbours and Naïve Bayes performed similarly, achieving 95% classification accuracy. The precision and accuracy of Support

Vector Machines was less than 90%, Table 8. The first measure refers to the number of accurate positive value predictions, while the second one is the number of correct predictions overall.

Table 7: Comparison of transportation mode classification performance using smartphones and machine learning techniques. Bayesian Network (BN), Support Vector Machines (SVM) and Neural Networks (NN) (Xiao et al., 2015).

	Classification performance	
	Training set	Test set
SVM	92.32%	85.65%
NN	91.95%	82.07%
BN	94.74%	92.74%

Table 8 : Transportation mode classification performance using smartphones and machine learning techniques. Neural Network (NN), K-Nearest Neighbour (KNN), Naïve Bayes (NB) and SVM classifiers (Eftekhari and Ghatee, 2016).

	Classification performance	
	Precision	Accuracy
Eftekhari and Ghatee, 2016	93	95
NN	93	95
KNN	94	95
NB	92	95
SVM	82	89

3.2 Travel time prediction

Accurate and reliable travel time prediction is crucial for drivers and ITS evaluation[3,4,5]. Traffic can

[3] https://ops.fhwa.dot.gov/publications/tt_reliability/TTR_Report.htm#overview
[4] https://citymapper.com/, accessed on 10/03/2018
[5] http://www.zipabout.com/, accessed on 10/03/2018

influence travel time heavily (Polson and Sokolov, 2017). Up to the end of the 2010s, the standard way of capturing traffic data was by fixed vehicle inductive loop presence detectors, a costly and inflexible solution (Vlahogianni et al., 2014, Vlahogianni, 2015).

Table 9 lists recent contributions on smartphone-based travel time prediction. The metrics used by the authors were not consistent, and a direct comparison of the methods was not possible. Notably, most contributions used crowd-sensing to build the travel time prediction model. In the majority, only the speed and GPS position were fused. Some authors highlighted the importance of weather and time at which travel takes place (Dobre and Xhafa, 2014 Amirian et al., 2016). In a comparison between least squares, K nearest neighbours, LARS, LASSO, Adaboost, gradient boosting and random forest methods, the last one showed the best performance (Amirian et al., 2016).

Table 9: Sensor fusion methods for smartphone-based prediction of travel time

Travel time prediction	**Signals**	**Method**	**Fusion**	**Noise**	**Feedback**	**Performance**
Campolo et al., 2012	GPS position, speed	n/a	LS	–	Compared to me	n/a
Tao and Manolopoulos, 2012	Position, speed	Simulation-based, Kalman filtering	CS	✓	Compared to me	- 85% correct allocation of road links and - 1.8 m/s mean absolute speed error
Tostes *et al.*, 2013	Map information	Image processing, logistic regression	CS	–	Compared to me	8% wrong classification of traffic flow
Ansar et al., 2014	GPS position, speed	SVR and Vector Matrix multiplication	CS	–	Compared to me	3.36-8.02% root mean distortion error
Dobre and Xhafa, 2014	Speed, GPS position, time, date	Linear interpolation	CS	–	Compared to me	80% accurate for 20% allowable error
Amirian *et al.*, 2016	Change of elevation, age, time of day, day of week, gender, weather condition	Least squares	CS	–	Compared to me	Prediction accuracy based on correlation R^2 : 0.64
		K nearest neighbours	CS	–	Compared to me	accuracy R^2 : 0.62
		LARS	CS	–	Compared to me	accuracy R^2 : 0.68
		LASSO	CS	–	Compared to me	accuracy R^2 : 0.69

		Elastic net	CS	–	Compared to me	accuracy R^2 : 0.69
		Adaboost	CS	–	Compared to me	accuracy R^2 : 0.70
		Gradient boosting	CS	–	Compared to me	accuracy R^2 : 0.71
		Random forest	CS	–	Compared to me	0.73
Woodard *et al.*, 2017	Speed, GPS position	Markov process	CS	✓	Compared to me	10% accurate travel time prediction

LS: Smartphone based fusion
CS: Crowd sensing based fusion
Noise: The method provides a probabilistic framework for rejecting noise and outliers contained in the signal
Compared to me: Feedback is provided to the driver using absolute metrics
Compared to all: Feedback is provided to the driver using relative metrics (compared to peers or drivers using the same routes)
LARS: least-angle regression
LASSO: lasso (least absolute shrinkage and selection operator)
R^2: linear correlation coefficient

3.3 Route choice prediction

Traffic regulators and local authorities can tremendously benefit by predicting commuters route choices. Multi-modal and flexible transportation solutions can be built based on this knowledge [6,7]. For the prediction, the GPS trace and map information are required (Shi and Liu, 2010, Sile et al., 2016). For high sampling frequencies (1 Hz) and good quality of GPS signal, the task is rather straightforward. However, due to the urban canyon effect or due to low sampling frequencies − for energy saving purposes − the GPS data acquired may be sparse. Sparsity can make the route choice identification and prediction more challenging. Table 10 compares different methods for identifying route choices. The metrics employed in the various studies differ. Hierarchical clustering based on crowd-sensing reported the best performance, 100% accuracy (Ciscal-Terry et al., 2016). For sensor fusion applied locally, the best performance was 91.3% with a combined Hidden Markov and Multinomial Logit Models (Jagadeesh and Srikanthan, 2017).

Table 10: Sensor fusion methods for smartphone-based identification of route choices

Route choice prediction	**Signals**	**Method**	**Fusion**	**Noise**	**Feedback**	**Performance**

[6] http://www.flexiroute.net/, accessed on 10/03/2018
[7] https://www.livetrekker.com, accessed on 10/03/2018

Miwa *et al*., 2012	GPS position, map information	Map matching	LS	–	Compared to me	90% accuracy ratio of plot match
Brazil *et al*., 2013	Drive Time, Drive Emission, Driving Habit, Drive Age, Drive Live, Rail Time, Rail Habit, Rail Age, Bus-Rail Time	Linear regression, rules	LS	–	Compared to me	R^2: 0.2379
Ciscal-Terry et al., 2016	Speed, GPS position, map information	Hierarchical cluster analysis	CS	–	Compared to all	100%
Fard *et al*. 2017	GPS position	Wavelets	LS	–	Compared to me	99% elimination of negative inter-vehicle distance
Jagadeesh and Srikanthan, 2017	GPS position, map information	Hidden Markov Model and Multinomial Logit Model	LS	✓	Compared to me	91.3 % accuracy
		Hidden Markov Model	LS	✓	Compared to me	89.6% accuracy
		Newson-Krumm	LS	✓	Compared to me	81.2% accuracy

LS: Smartphone based fusion
CS: Crowd sensing based fusion
Noise: The method provides a probabilistic framework for rejecting noise and outliers contained in the signal
Compared to me: Feedback is provided to the driver using absolute metrics
Compared to all: Feedback is provided to the driver using relative metrics (compared to peers or drivers using the same routes)
R^2: linear correlation coefficient

3.4 Driver aggressiveness classification

Behaviour at the tactical level refers to driver actions that last a few seconds, such as car following, lane change and overtaking (Michon, 1985). Tactical driving behaviour can influence heavily road safety, traffic flow smoothness and fuel consumption. Two main aspects of tactical behaviour were reviewed: driver aggressiveness and eco-friendliness. Studies showed that aggressiveness and eco-friendliness are interrelated, though not identical (Alessandrini et al., 2009; Sivak, M. & Schoettle, 2012). Some smartphone applications were developed for improving tactical driving behaviour[8,9]. There are no standards for characterising tactical driving, and to this end, some metrics (and their combination) have been proposed. The most popular ones are listed in Table 11 (Handel *et al*., 2014).

[8] https://www.aviva.co.uk/car-insurance/drive/, accessed on 10/03/2018
[9] https://motormate-by-confused-com.soft112.com/, accessed on 10/03/2018

Table 11: Features for characterising driver tactical behaviour (Handel et al., 2014)

Metric	Description
Acceleration (positive longitudinal acceleration)	Number of rapid acceleration events and harshness
Braking (negative longitudinal acceleration)	Number of harsh braking events and harshness
Speeding (absolute)	Amount of absolute speeding
Speeding (relative)	Amount of speeding relative to a location dependent limit
Smoothness (variance of acceleration)	Long-term speed variations around a nominal speed
Swerving (lateral acceleration)	Number of abrupt steering manoeuvres and their harshness
Cornering	Number of events when turning at too high speed and their harshness
Eco-ness	Instantaneous or trip-based energy consumption or carbon footprint
Elapsed time	Time duration of the trip
Elapsed distance	Distance of the trip
Time of day	Actual time of day when making the trip
Location	Geographical location of the trip

Due to the arbitrary position of a smartphone inside a vehicle, it is required to re-orient the smartphone signals along the vehicle's coordinate system. This should be done at the beginning of each route and each time the smartphone changes orientation. Re-orientation is achieved by fusing the accelerometer, gyroscope and magnetometer signals and calculating the Euler angles. Re-orientation can also be achieved by fusing only the accelerometer and magnetometer signals[10]. Because the accelerometer and gyroscope signals are noisy, it has been suggested to re-orient the signals using the average values of the Euler angles (Vlahogianni and Barmpounakis, 2017).

The variety of driving styles and the fact that smartphone sensor signals are noisy, make difficult to distinguish ordinary events from dangerous ones. Table 12, provides a summary of approaches found in our literature review. For the classification task various machine learning methods were proposed including rough set theory, decision tree C4.5, Neural Networks, Support Vector Machines, Random Forrest and Bayesian Networks (Ferreira *et al.*, 2017). Rough set theory and Random Forrest methods achieved the best performance with 99.4% event detection and Area Under Curve (AUC) in the Receiver Operating Characteristic graph higher than 0.98, respectively.

Table 12: Sensor fusion methods for smartphone-based monitoring of aggressive driver behaviour

[10] https://www.nxp.com/docs/en/application-note/AN3461.pdf, accessed on 10/03/2018

Aggressive driving classification	Signals	Method	Fusion	Noise	Feedback	Performance
Fazeen et al, 2012	Acceleration		LS	–	Compared to me	
Zeeman and Booysen, 2013	Speed, acceleration	Rule based	LS	–	Compared to me	n/a
Zhu *et al*. 2013/	Speed, acceleration,	Clustering	LS	–	Compared to me, Compared to all	n/a
Castignani and Derrmann, 2015	Acceleration, orientation, GPS speed, GPS heading	Fuzzy logic	LS	–	Compared to me	TPR>90%
Daptardar et al., 2015	Acceleration, gyroscope	Hidden Markov Model, Jerk Energy	LS	–	Compared to me	95% accuracy
Predic and Stojanovic, 2015	GPS position, acceleration	Decision trees, clustering	CS	–	Compared to all	80-100% precision
Saiprasert *et al*., 2015	GPS position, speed, orientation, acceleration	Rule-based	LS	–	Compared to me	Detects 8 out of 12 driving event types
		Dynamic Time Warping	LS	–	Compared to me	• Detects 11 out of 12 driving event types • Detection rate between 37.5-100%.
		Self-Triggered Dynamic Time Warping	LS	–	Compared to me	• Detects 8 out of 12 driving event types • Detection rate between 0-80%.
Vlahogianni and Barmpounakis, 2017	Acceleration, speed, speed variance, GPS position, map information	Rough set theory	LS	✓	Compared to me	99.4 % event detection accuracy TPR: 88.1% FPR: 0.3%
Júnior *et al*., 2017	Accelerometer, gyroscope, magnetometer	Random Forrest	CS	✓	Compared to me	AUC>0.98 in ROC
Meng *et al*. 2014	Accelerometer, map information	Speed estimation using crowdsourced data	CS	–	Compared to all	>94% accuracy
Singh *et al*., 2017	Accelerometer, gyroscope	Dynamic Time Warping	LS	–	Compared to all	100% braking events 97% normal turns 87% aggressive turns

LS: Smartphone based fusion
CS: Crowd sensing based fusion
Noise: The method provides a probabilistic framework for rejecting noise and outliers contained in the signal
Compared to me: Feedback is provided to the driver using absolute metrics
Compared to all: Feedback is provided to the driver using relative metrics (compared to peers or drivers using the same routes)
TPR: True Positive Rate
AUC: Area Under Curve
ROC: Receiver Operating Characteristics diagram

3.5 Driver eco-friendliness classification

The largest contributor to global warming, by subsector, is road transport[11]. From the current vehicle fleet, only a small percentage is equipped with a technology that can inform drivers about their driving behaviour and how eco-friendly it is. Instead, numerous smartphone applications are available for this purpose[12,13,14]. Eco-friendly driving is mainly dependent on vehicle speed, acceleration profiles and the engine's efficiency at the operating points (Ehsani *et al.*, 2016).

Table 13 summarises various smartphone-based approaches for detecting and improving eco-friendly driving. Central to the accurate fuel consumption estimation is the correct estimation of gear changes, because this determines the engine speed and thus engine efficiency. Most of the trials that tried to achieve this without using On Board Diagnostic (OBD) information deemed unsuccessful. More accurate approaches were developed combining smartphone measurements and OBD signals such as mass flow sensor, manifold absolute pressure, and intake air temperature (Magana and Munoz-Organero, 2016). To retrieve the additional OBD information it is currently necessary to install additional hardware. This requirement restricts scalability. Although it is not expensive it is not handy and may pose a threat from a Cybersecurity point of view (Cheah *et al.*, 2017).

According to the literature, the potential fuel consumption savings by improving driver eco-friendliness using smartphones are significant, ranging between 3-30%. A recent study using in-vehicle data recorders reported potential energy savings in the range 3-10% (Toledo and Shiftan, 2016). Apparently, the improvement depends on the driver behaviour and estimation accuracy. The latter depends on the vehicle model. In case, a validated vehicle model is used the error can be negligible. In the opposite, the error was approximately 10% of the actual value.

Table 13: Sensor fusion methods for smartphone-based classification of eco-friendly driver behaviour

Eco-friendly driving classification	**Signals**	**Method**	**Fusion**	**Noise**	**Feedback**	**Performance**

[11] http://www.who.int/sustainable-development/transport/health-risks/air-pollution/en/, accessed on 10/03/2018
[12] http://ecodrive.driveuconnect.eu/, accessed on 10/03/2018
[13] https://www.geco-drive.fr/, accessed on 10/03/2018
[14] http://www.play-ecodriver.ch/en, accessed on 10/03/2018

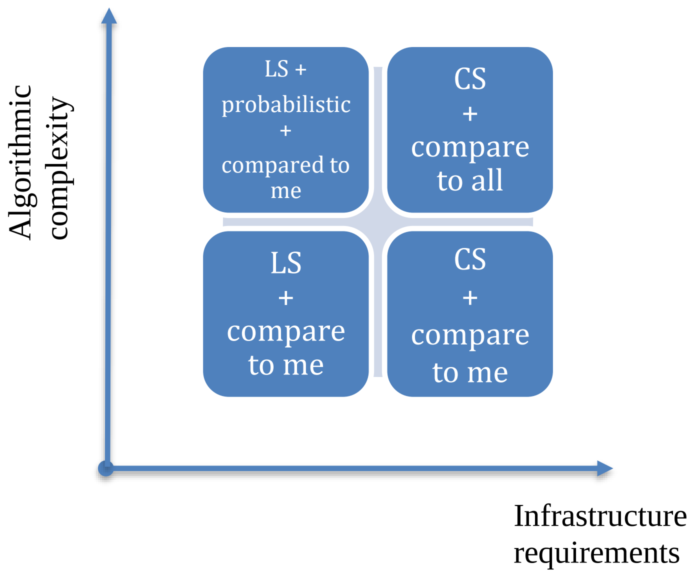
Li *et al*., 2012	GPS position, speed, acceleration. jerk	Wavelet denoising, decision tree, vehicle model	LS	✓	Compared to me	0.99 correlation, MAE≈0.08 kg fuel consumption estimation
Tulusan *et al*., 2012	Acceleration, average speed, gear change	Simulation-based	LS	−	Compared to me	3.23% fuel consumption improvement
Diaz *et al*., 2014	GPS position, speed, acceleration, jerk, acceleration, gyrometer	Neural networks	LS	−	Compared to me	11.7% accurate fuel consumption estimation
Skog *et al*., 2014	GPS speed, altitude, vehicle parameters	Vehicle model based, polynomial regression models	LS	−	Compared to me	• root mean square error of ~0.3 [g/s], • normalised mean square error ≈10%
Astarita *et al*., 2015	Speed, acceleration, GPS position, fuel consumption	Mapping	CS	−	Compared to all	9.5-13.5% fuel consumption error
Orfila *et al*., 2015	Acceleration, speed variation, gear change	Rule-based	CS	−	Compared to all	30% fuel consumption improvement
Magana and Munoz-Organero, 2016	Vehicle speed, engine speed, engine load, mass air flow, throttle position, travel distance, smartphone camera, GPS sensor, weather information	Multilayer Perceptrons, Naïve Bayes, C4.5, fuzzy logic, clustering	LS	−	Compared to all	11.4% fuel consumption improvement
Meseguer *et al*. 2017	Acceleration, engine revolutions per minute, speed, mass flow sensor, manifold absolute pressure, and intake air temperature	Neural networks	CS	−	Compared to all	15- 20% fuel consumption improvement

LS: Smartphone based fusion
CS: Crowd sensing based fusion
Noise: The method provides a probabilistic framework for rejecting noise and outliers contained in the signal
Compared to me: Feedback is provided to the driver using absolute metrics
Compared to all: Feedback is provided to the driver using relative metrics (compared to peers or drivers using the same routes)
MAE: Mean Absolute Error

4 Discussion and critical analysis

The literature survey confirmed the increasing academic and industrial interest in using smartphones for the development of personalised Intelligent Transportation Applications. Recent publications on monitoring driver behaviour using smartphones were compared using the Cybernetics paradigm. The analysis comprised three parts. The first part concerned the signals fused, the second the signal processing/classification method and the third one the scale at which sensor fusion took place (crowd sensing or smartphone based). As a general remark, the experiments conducted and the metrics used in the contributions were different and non-standard. Furthermore, many of the useful details on the implementation of the classification methods were not reported. Therefore, a direct comparison was not possible. Nevertheless, Fig. 5 provides a qualitative assessment of the sensor fusion algorithms reviewed, with respect to the reported algorithmic complexity and infrastructure requirements. LS denotes local sensing and CS crowd-sensing. “Compared to me” refers to driver evaluation based solely on its own data, while “compared to all” when the comparison is made with respect to other drivers. To accelerate research in the field, it will be required to set up a standard framework that will allow direct comparison of the methods. As a first step, making the data and code used in a study publicly available will contribute significantly in this direction.

Fig. 5: Qualitative assessment of reviewed smartphone sensor fusion algorithms with respect to algorithmic complexity and infrastructure requirements



Interestingly, most contributions considered only one aspect of driver behaviour; an integrated approach is currently lacking. This may potentially lead to biased assessments. For example, the battery energy savings due to lower GPS sampling frequency for monitoring one element may not hold if the sampling frequency needs to be higher for monitoring another one. For an integrated approach, the most commonly used parameters are the position, speed and acceleration. Thus, it is crucial to estimate these variables as accurate as possible and appreciate their uncertainty. In general, acceleration can be measured directly using the smartphone's accelerometers or by differentiating the GPS speed. The position can be provided using the GPS signal or cameras and map information. The only variable for which a second source of information is not available is speed. Potentially this can be retrieved from the vehicle's OBD, but currently, there is no method to achieve this without additional hardware.

In sensor fusion, signals with low uncertainty should have more influence when fused compared to those that are more uncertain (Li et al., 2013). Standard techniques like Kalman Filter require *a priori* the definition of a noise covariance matrix to take this into account. In general, it is difficult to build or tune the matrix if the sensor characteristics are not known or calibrated, which is the case with smartphones (Gibbs, 2011). Neural Networks, during the training phase, learn to ignore spurious data and therefore take data quality implicitly into account (Cao *et al*., 2018). Surprisingly, in most crowd-sensing based ITS applications, the signal uncertainty is not taken into consideration. The signals are uploaded in raw form and then fused; with equal importance.

In the following we highlight potential future research directions and refer to successful paradigms found in other domains.

4.1 Fusion of heterogeneous information

Advanced sensor fusion can lead to significant accuracy improvements without additional hardware. A possible direction is the fusion of infrastructure/roadside information. There, several opportunities exist, for example by exploiting fingerprinting techniques, Bluetooth detectors presence, magnetic sensing and information-rich satellite signal (Canciani and Raquet, 2016; Kulshrestha et al., 2017; Nurmi et al., 2017). Some of these techniques were proved useful in an indoor or controller environment, but it is necessary to examine how these techniques perform outdoors. Fusion of information-rich signals that include not just sensor signals but also contextual information, such as weather condition and social network semantic analysis, can improve traffic congestion estimates and travel time prediction. Some approaches in this direction were developed but are more qualitative than quantitative (Tse et al., 2017a, 2017b; Wang et al., 2017).

4.2 Sparse reconstruction & Deep learning

The mobile data traffic is expected to reach 30.6 billion gigabytes by 2020[15]. The explosion of data volume has a led to a problem which is also known as Garbage In – Garbage Out (GIGO) Big Data Analysis[16] . For the transportation industry, this is an even bigger problem due to the associated cost of transmitting the data. There is a need to develop intelligent smartphone algorithms that can filter streamlined data and detect informative events. It will reduce the requirement to transmit all the raw data centrally but the most informative features (Kanarachos et al., 2015; Martinez et al., 2017; Mirsky et al., 2017; Vasconcelos et al., 2017). In this context, a promising direction is compressive sensing and similar algorithms. Compressive sensing is a relatively new signal processing algorithm that allows the reconstruction of a signal using fewer samples than those suggested by the Shannon-Nyquist frequency sampling theorem. (Z. Liu et al., 2016; Razzaque and Clarke, 2016).

The implementation of Deep Learning algorithms for processing smartphone data for ITS is expected to increase considerably as Deep Neural Networks are ideally suited for handling noisy sensor data and detecting underlying patterns. Successful examples not based on smartphone data or with a different scope were recently developed (Fang et al., 2017; Kanarachos et al., 2017; Munoz-Organero et al., 2017; Xiao et al., 2017; Xu et al., 2017).

4.3 Data credibility & sparse crowd-sensing

Currently, most ITS crowd-sensing approaches upload data in raw form to a central server and subsequently post processing takes place. Although this approach may be satisfactory for an application with a massive number of users, it is questionable whether it is a suitable when the input

---

[15] https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/mobile-white-paper-c11-520862.html, accessed on 10/03/2018
[16] http://www.ibmbigdatahub.com/blog/garbage-garbage-out, accessed on 10/03/2018

is sparse and infrequent. For example, this happens when deployment is at early stages (density of information is low) or in cases where quick response time is critical (long term accumulation of information is not acceptable). In these cases, also known as sparse crowd sensing applications, acknowledgment of the quality of information is extremely important for the quality of service. Paradigms found in other domains need to be investigated and transferred to smartphone-based ITS applications (Hao et al., 2017; Kang et al., 2017; Restuccia et al., 2017; Shao et al., 2015; Zamora et al., 2016).

To this end, it will be also required to investigate and develop data management frameworks that guarantee or improve data credibility over time. Methods that can assess the credibility of information sources will increasingly gain importance (Miao et al., 2016; Ren et al., 2015; Zhou et al., 2017). In this context, it will be required to investigate flexible sensor fusion methods capable of selecting ad-hoc sensor sets depending on the application requirements, costs and context (Francois Schnitzler et al., 2015; Shen et al., 2017).

5 Conclusions

The present survey reviewed recent scientific contributions in the field of smartphone-based monitoring of driver behaviour. The focus was on sensor fusion techniques and the use of smartphones as an integrated platform for monitoring driver behaviour. In particular, transportation mode classification, route choice prediction, travel time estimation, as well as aggressive and eco-friendly driving identification were reviewed. The theoretical framework for the analysis was the Cybernetics model according to which actions depend on a repetitive cycle: sensing, information processing, decision making and feedback.

- Smartphones and their sensors are increasingly used as devices for monitoring driver behaviour. However, an integrated approach comprising multiple aspects is currently missing.

- Smartphones present competitive advantages because of their high market penetration, Internet of Things connectivity and data sharing capability. The analysis revealed that these competitive advantages are not always exploited.
- Various machine learning algorithms have been researched for fusing and discovering knowledge in smartphone data. However, Deep Learning methods have not been, up to now, exploited thoroughly. Deep Learning is particularly suitable for knowledge discovery and spatiotemporal correlation of multivariate data.
- In crowd-sensing ITS applications, data are usually uploaded in raw form and centrally fused. This has two immediate negative consequences. First, the quality of service is severely reduced when the density of information is low or time criticality is high. Second, the volume of data is increased unnecessarily and thereby the communication and storage cost. In this context, it is expected that future research should be directed in developing smartphone-based methods that consider data source credibility, select optimal sets of sensor and information sources and intelligently exploit signal recovery methods that reduce data volumes.

ACKNOWLEDGMENTS

The authors would like to thank Intelligent Variable Message Systems (iVMS), funded by the Government's Local Growth Fund through Coventry and Warwickshire Local Enterprise Partnership.

CONFLICT OF INTEREST STATEMENT

Conflicts of interest: none

References

Akherfi, K., Gerndt, M. and Harroud, H. (2018). Mobile cloud computing for computation offloading: Issues and challenges. Applied Computing and Informatics, 14(1), pp.1-16.

Alessandrini, A., Orecchini, F., Ortenzi, F. & Campbell, F.V. 2009, "Drive-style emissions testing on the latest two Honda hybrid technologies", European Transport Research Review, vol. 1, no. 2, pp. 57-66.
Aly, H., Basalamah, A. & Youssef, M. 2016, "Robust and ubiquitous smartphone-based lane detection", Pervasive and Mobile Computing, vol. 26, pp. 35-56.
Amirian, P., Basiri, A. & Morley, J. 2016, "Predictive analytics for enhancing travel time estimation in navigation apps of apple, google, and microsoft", Proceedings of the 9th ACM SIGSPATIAL International Workshop on Computational Transportation Science, IWCTS 2016, pp. 31.
Anagnostopoulos, T., Ferreira, D., Samodelkin, A., Ahmed, M., Kostakos, V., 2016. Cyclist-aware traffic lights through distributed smartphone sensing. Pervasive Mob. Comput. 31, 22–36. doi:10.1016/j.pmcj.2016.01.012
Assemi, B., Safi, H., Mesbah, M. & Ferreira, L. 2016, "Developing and Validating a Statistical Model for Travel Mode Identification on Smartphones", IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 7, pp. 1920-1931.
Astarita, V., Guido, G., Mongelli, D. & Giofrè, V.P. 2015, "A co-operative methodology to estimate car fuel consumption by using smartphone sensors", Transport, vol. 30, no. 3, pp. 307-311.
Bareth, U., Kupper, A., 2011. Energy-Efficient Position Tracking in Proactive Location-Based Services for Smartphone Environments, in: 2011 IEEE 35th Annual Computer Software and Applications Conference. Presented at the 2011 IEEE 35th Annual Computer Software and Applications Conference, pp. 516–521. doi:10.1109/COMPSAC.2011.72
Bento, L.C., Bonnifait, P., Nunes, U.J., 2017. Cooperative GNSS positioning aided by road-features measurements. Transp. Res. Part C Emerg. Technol. 79, 42–57. doi:10.1016/j.trc.2017.01.002
Ben-Zeev, D., Scherer, E.A., Wang, R., Xie, H., Campbell, A.T., 2015. Next-generation psychiatric assessment: Using smartphone sensors to monitor behavior and mental health. Psychiatr. Rehabil. J. 38, 218–226. doi:10.1037/prj0000130
Bierlaire, M., Chen, J. & Newman, J. 2013, "A probabilistic map matching method for smartphone GPS data", Transportation Research Part C: Emerging Technologies, vol. 26, pp. 78-98.
Biljecki, F., Ledoux, H., van Oosterom, P., 2013. Transportation mode-based segmentation and classification of movement trajectories. Int. J. Geogr. Inf. Sci. 27, 385–407. doi:10.1080/13658816.2012.692791
Brazil, W. & Caulfield, B. 2013, "Does green make a difference: The potential role of smartphone technology in transport behaviour", Transportation Research Part C: Emerging Technologies, vol. 37, pp. 93-101.
Canciani, A., Raquet, J., 2016. Absolute Positioning Using the Earth's Magnetic Anomaly Field. Navigation 63, 111–126. doi:10.1002/navi.138
Cao, W., Wang, X., Ming, Z. & Gao, J. 2018, "A review on neural networks with random weights", Neurocomputing, vol. 275, pp. 278-287.
Castignani, G., Derrmann, T., Frank, R. & Engel, T. 2015, "Driver behavior profiling using smartphones: A low-cost platform for driver monitoring", IEEE Intelligent Transportation Systems Magazine, vol. 7, no. 1, pp. 91-102.
Cheah, M., Shaikh, S., Haas, O. and Ruddle, A. (2017). Towards a systematic security evaluation of the automotive Bluetooth interface. Vehicular Communications, 9, pp.8-18.
Chen, D., Cho, K.-T., Han, S., Jin, Z., Shin, K.G., 2015. Invisible Sensing of Vehicle Steering with Smartphones, in: Proceedings of the 13th Annual International Conference on Mobile Systems, Applications, and Services, MobiSys '15. ACM, New York, NY, USA, pp. 1–13. doi:10.1145/2742647.2742659
Chong, L., Abbas, M.M., Medina Flintsch, A., Higgs, B., 2013. A rule-based neural network approach to model driver naturalistic behavior in traffic. Transp. Res. Part C Emerg. Technol. 32, 207–223. doi:10.1016/j.trc.2012.09.011

Chowdhury, A., Ghose, A., Chakravarty, T. & Balamuralidhar, P. 2016, An improved fusion algorithm for estimating speed from smartphone’s Ins/Gps sensors.
Christopoulos, S.G., Kanarachos, S. & Chroneos, A. 2018, "Learning Driver Braking Behavior Using Smartphones, Neural Networks and the Sliding Correlation Coefficient: Road Anomaly Case Study", IEEE Transactions on Intelligent Transportation Systems, .
Ciscal-Terry, W., Dell’Amico, M., Hadjidimitriou, N.S., Iori, M., 2016. An analysis of drivers route choice behaviour using GPS data and optimal alternatives. J. Transp. Geogr. 51, 119–129. doi:10.1016/j.jtrangeo.2015.12.003
Comer, J.C., Wikle, T.A., 2008. Worldwide Diffusion of the Cellular Telephone, 1995–2005. Prof. Geogr. 60, 252–269. doi:10.1080/00330120701836303
Dabove, P., Ghinamo, G., Lingua, A.M., 2015. Inertial sensors for smartphones navigation. SpringerPlus 4, 834. doi:10.1186/s40064-015-1572-8
Dabiri, S. & Heaslip, K. 2018, "Inferring transportation modes from GPS trajectories using a convolutional neural network", Transportation Research Part C: Emerging Technologies, vol. 86, pp. 360-371.
Daptardar, S., Lakshminarayanan, V., Reddy, S., Nair, S., Sahoo, S. & Sinha, P. 2015, "Hidden Markov Model based driving event detection and driver profiling from mobile inertial sensor data", 2015 IEEE SENSORS - Proceedings.Diaz Alvarez, A., Serradilla Garcia, F., Naranjo, J., Anaya, J. and Jimenez, F. (2014). Modeling the Driving Behavior of Electric Vehicles Using Smartphones and Neural Networks. IEEE Intelligent Transportation Systems Magazine, 6(3), pp.44-53.
Eftekhari, H.R., Ghatee, M., 2016. An inference engine for smartphones to preprocess data and detect stationary and transportation modes. Transp. Res. Part C Emerg. Technol. 69, 313–327. doi:10.1016/j.trc.2016.06.005
Ehsani, M., Ahmadi, A. and Fadai, D. (2016). Modeling of vehicle fuel consumption and carbon dioxide emission in road transport. Renewable and Sustainable Energy Reviews, 53, pp.1638-1648.
Espada, J.P., García-Díaz, V., Crespo, R.G., Pelayo G-Bustelo, B.C., Cueva Lovelle, J.M., 2014. Improving the GPS Location Quality Using a Multi-agent Architecture Based on Social Collaboration, in: Wen, Z., Li, T. (Eds.), Practical Applications of Intelligent Systems: Proceedings of the Eighth International Conference on Intelligent Systems and Knowledge Engineering, Shenzhen, China, Nov 2013 (ISKE 2013). Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 371–379. doi:10.1007/978-3-642-54927-4_35
Fang, S.H., Fei, Y.X., Xu, Z., Tsao, Y., 2017. Learning Transportation Modes From Smartphone Sensors Based on Deep Neural Network. IEEE Sens. J. 17, 6111–6118. doi:10.1109/JSEN.2017.2737825
Fazeen, M., Gozick, B., Dantu, R., Bhukhiya, M. and González, M. (2012). Safe Driving Using Mobile Phones. IEEE Transactions on Intelligent Transportation Systems, 13(3), pp.1462-1468.
Ferreira, J., Júnior, Carvalho, E., Ferreira, B.V., de Souza, C., Suhara, Y., Pentland, A., Pessin, G., 2017. Driver behavior profiling: An investigation with different smartphone sensors and machine learning. PLOS ONE 12, e0174959. doi:10.1371/journal.pone.0174959
Francois Schnitzler, Jia Yuan Yu, Shie Mannor, 2015. Sensor Selection for Crowdsensing Dynamical Systems, in: Guy Lebanon, S. V. N. Vishwanathan (Eds.), Proceedings of the Eighteenth International Conference on Artificial Intelligence and Statistics. PMLR, pp. 829–837.
Ganti, R.K., Ye, F., Lei, H., 2011. Mobile crowdsensing: current state and future challenges. IEEE Commun. Mag. 49, 32–39. doi:10.1109/MCOM.2011.6069707
Gibbs, B.P., 2011. Kalman Filtering, in: Advanced Kalman Filtering, Least-Squares and Modeling. John Wiley & Sons, Inc., pp. 289–342. doi:10.1002/9780470890042.ch8
Groves, P.D., 2011. Shadow Matching: A New GNSS Positioning Technique for Urban Canyons. J. Navig. 64, 417–430. doi:10.1017/S0373463311000087

Guido, G., Gallelli, V., Saccomanno, F., Vitale, A., Rogano, D., Festa, D., 2014. Treating uncertainty in the estimation of speed from smartphone traffic probes. Spec. Issue Effic. Reliab. Transp. Syst. 47, 100–112. doi:10.1016/j.trc.2014.07.003
Handel, P., Skog, I., Wahlstrom, J., Bonawiede, F., Welch, R., Ohlsson, J., Ohlsson, M., 2014. Insurance Telematics: Opportunities and Challenges with the Smartphone Solution. IEEE Intell. Transp. Syst. Mag. 6, 57–70. doi:10.1109/MITS.2014.2343262
Hao, X., Xu, L., Lane, N.D., Liu, X., Moscibroda, T., 2017. Density-aware Compressive Crowdsensing, in: Proceedings of the 16th ACM/IEEE International Conference on Information Processing in Sensor Networks, IPSN '17. ACM, New York, NY, USA, pp. 29–39. doi:10.1145/3055031.3055081
Humphreys, T.E., Murrian, M., Diggelen, F. van, Podshivalov, S., Pesyna, K.M., 2016. On the feasibility of cm-accurate positioning via a smartphone's antenna and GNSS chip, in: 2016 IEEE/ION Position, Location and Navigation Symposium (PLANS). pp. 232–242. doi:10.1109/PLANS.2016.7479707
Jagadeesh, G.R. & Srikanthan, T. 2017, "Online Map-Matching of Noisy and Sparse Location Data with Hidden Markov and Route Choice Models", IEEE Transactions on Intelligent Transportation Systems, vol. 18, no. 9, pp. 2423-2434.
Kanarachos, S., Christopoulos, S.-R.G., Chroneos, A., Fitzpatrick, M.E., 2017. Detecting anomalies in time series data via a deep learning algorithm combining wavelets, neural networks and Hilbert transform. Expert Syst. Appl. 85, 292–304. doi:10.1016/j.eswa.2017.04.028
Kanarachos, S., Mathew, J., Chroneos, A., Fitzpatrick, M.E., 2015. Anomaly detection in time series data using a combination of wavelets, neural networks and Hilbert transform. Presented at the 6th IEEE International Conference on Information, Intelligence, Systems and Applications (IISA2015), IEEE, Corfu, Greece.
Kang, X., Liu, L., Ma, H., 2017. Enhance the Quality of Crowdsensing for Fine-Grained Urban Environment Monitoring via Data Correlation. Sensors 17. doi:10.3390/s17010088
Khan, W.Z., Xiang, Y., Aalsalem, M.Y., Arshad, Q., 2013. Mobile Phone Sensing Systems: A Survey. IEEE Commun. Surv. Tutor. 15, 402–427. doi:10.1109/SURV.2012.031412.00077
Kulshrestha, T., Saxena, D., Niyogi, R., Raychoudhury, V., Misra, M., 2017. SmartITS: Smartphone-based identification and tracking using seamless indoor-outdoor localization. J. Netw. Comput. Appl. 98, 97–113. doi:10.1016/j.jnca.2017.09.003
Li, K., Lu, M., Lu, F., Lv, Q., Shang, L. & Maksimovic, D. 2012, Personalized driving behavior monitoring and analysis for emerging hybrid vehicles.
Li, L., Quddus, M., Zhao, L., 2013. High accuracy tightly-coupled integrity monitoring algorithm for map-matching. Transp. Res. Part C Emerg. Technol. 36, 13–26. doi:10.1016/j.trc.2013.07.009
Lin, A., Zhang, J., Lu, K., Zhang, W., 2014. An efficient outdoor localization method for smartphones, in: 2014 23rd International Conference on Computer Communication and Networks (ICCCN). Presented at the 2014 23rd International Conference on Computer Communication and Networks (ICCCN), pp. 1–8. doi:10.1109/ICCCN.2014.6911788
Liu, J., Priyantha, B., Hart, T., Jin, Y., Lee, W., Raghunathan, V., Ramos, H.S., Wang, Q., 2016. CO-GPS: Energy Efficient GPS Sensing with Cloud Offloading. IEEE Trans. Mob. Comput. 15, 1348–1361. doi:10.1109/TMC.2015.2446461
Liu, Z., Wu, M., Zhu, K., Zhang, L., 2016. SenSafe: A Smartphone-Based Traffic Safety Framework by Sensing Vehicle and Pedestrian Behaviors. Mob. Inf. Syst. 2016, 1–13. doi:10.1155/2016/7967249
Martin, B.D., Addona, V., Wolfson, J., Adomavicius, G. & Fan, Y. 2017, "Methods for real-time prediction of the mode of travel using smartphone-based GPS and accelerometer data", Sensors (Switzerland), vol. 17, no. 9.
Martinez, M., Leon, P.L.D., Keeley, D., 2017. Novelty detection for predicting falls risk using smartphone gait data, in: 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). pp. 2202–2206. doi:10.1109/ICASSP.2017.7952547

Merchant, G., 2012. Mobile practices in everyday life: Popular digital technologies and schooling revisited. Br. J. Educ. Technol. 43, 770–782. doi:10.1111/j.1467-8535.2012.01352.x

Menard, T., Miller, J., Nowak, M. & Norris, D. 2011, "Comparing the GPS capabilities of the Samsung Galaxy S, Motorola Droid X, and the Apple iPhone for vehicle tracking using FreeSim-Mobile", IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC, pp. 985.

Menard, T. & Miller, J. 2011, "Comparing the GPS capabilities of the iPhone 4 and iPhone 3G for vehicle tracking using FreeSim-Mobile", IEEE Intelligent Vehicles Symposium, Proceedings, pp. 278.

Miao, C., Yu, H., Shen, Z., Leung, C., 2016. Balancing quality and budget considerations in mobile crowdsourcing. Decis. Support Syst. 90, 56–64. doi:10.1016/j.dss.2016.06.019

Michon, J.A., 1985. A Critical View of Driver Behavior Models: What Do We Know, What Should We Do?, in: Evans, L., Schwing, R.C. (Eds.), Human Behavior and Traffic Safety. Springer US, Boston, MA, pp. 485–524. doi:10.1007/978-1-4613-2173-6_19

Mirsky, Y., Shabtai, A., Shapira, B., Elovici, Y., Rokach, L., 2017. Anomaly detection for smartphone data streams. Pervasive Mob. Comput. 35, 83–107. doi:10.1016/j.pmcj.2016.07.006

Morillo, M.L., Gonzalez-Abril, L., Ramirez, A.J., de la Concepcion, A.M., 2015. Low Energy Physical Activity Recognition System on Smartphones. Sensors 15. doi:10.3390/s150305163

Munoz-Organero, M., Ruiz-Blaquez, R., Sánchez-Fernández, L., 2017. Automatic detection of traffic lights, street crossings and urban roundabouts combining outlier detection and deep learning classification techniques based on GPS traces while driving. Comput. Environ. Urban Syst. doi:10.1016/j.compenvurbsys.2017.09.005

Noureldin, A., El-Shafie, A., Bayoumi, M., 2011. GPS/INS integration utilizing dynamic neural networks for vehicular navigation. Spec. Issue Intell. Transp. Syst. 12, 48–57. doi:10.1016/j.inffus.2010.01.003

Nurmi, J., Lohan, E.-S., Wymeersch, H., Seco-Granados, G., Nykänen, O. (Eds.), 2017. Multi-Technology Positioning. Springer International Publishing. doi:10.1007/978-3-319-50427-8

Oshin, T.O., Poslad, S., Ma, A., 2012. Improving the Energy-Efficiency of GPS Based Location Sensing Smartphone Applications, in: 2012 IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications. Presented at the 2012 IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications, pp. 1698–1705. doi:10.1109/TrustCom.2012.184

Polson, N.G., Sokolov, V.O., 2017. Deep learning for short-term traffic flow prediction. Transp. Res. Part C Emerg. Technol. 79, 1–17. doi:10.1016/j.trc.2017.02.024

Predic, B. & Stojanovic, D. 2015, "Enhancing driver situational awareness through crowd intelligence", Expert Systems with Applications, vol. 42, no. 11, pp. 4892-4909.

Razzaque, M.A., Clarke, S., 2016. Compression-based energy efficient sensor data gathering framework for smartphones, in: 2016 International Wireless Communications and Mobile Computing Conference (IWCMC). pp. 126–132. doi:10.1109/IWCMC.2016.7577045

Ren, J., Zhang, Y., Zhang, K., Shen, X. (Sherman), 2015. SACRM: Social Aware Crowdsourcing with Reputation Management in mobile sensing. Mob. Ubiquitous Sens. Soc. Netw. Viewp. 65, 55–65. doi:10.1016/j.comcom.2015.01.022

Restuccia, F., Ghosh, N., Bhattacharjee, S., Das, S., Melodia, T., 2017. Quality of Information in Mobile Crowdsensing: Survey and Research Challenges. ArXiv E-Prints.Saiprasert, C., Pholprasit, T. & Thajchayapong, S. 2017, "Detection of Driving Events using Sensory Data on Smartphone", International Journal of Intelligent Transportation Systems Research, vol. 15, no. 1, pp. 17-28.

Semanjski, I., Gautama, S., 2016. Crowdsourcing mobility insights – Reflection of attitude based segments on high resolution mobility behaviour data. Transp. Res. Part C Emerg. Technol. 71, 434–446. doi:10.1016/j.trc.2016.08.016

Shaikh, A.A., Karjaluoto, H., 2015. Mobile banking adoption: A literature review. Telemat. Inform. 32, 129–142. doi:10.1016/j.tele.2014.05.003

Shao, L., Wang, C., Jiang, C., 2015. STC: Coarse-Grained Vehicular Data Based Travel Speed Sensing by Leveraging Spatial-Temporal Correlation. ArXiv E-Prints.

Shen, W., Li, S., Yang, J., Dou, W., Ni, Q., 2017. A Participant Selection Method for Crowdsensing Under an Incentive Mechanism, in: Wang, S., Zhou, A. (Eds.), Collaborate Computing: Networking, Applications and Worksharing: 12th International Conference, CollaborateCom 2016, Beijing, China, November 10–11, 2016, Proceedings. Springer International Publishing, Cham, pp. 557–562. doi:10.1007/978-3-319-59288-6_54

Shi, W. & Liu, Y. 2010, "Real-time urban traffic monitoring with global positioning system-equipped vehicles", IET Intelligent Transport Systems, vol. 4, no. 2, pp. 113-120.

Shuib, L., Shamshirband, S., Ismail, M.H., 2015. A review of mobile pervasive learning: Applications and issues. Comput. Hum. Behav. 46, 239–244. doi:10.1016/j.chb.2015.01.002

Siła-Nowicka, K., Vandrol, J., Oshan, T., Long, J.A., Demšar, U. & Fotheringham, A.S. 2016, "Analysis of human mobility patterns from GPS trajectories and contextual information", International Journal of Geographical Information Science, vol. 30, no. 5, pp. 881-906.

Simpkins, C.A., Simpkins, A.M., 2012. Cybernetics: Or Control and Communications in the Animal and the Machine (Wiener, N.) [On the Shelf]. IEEE Robot. Autom. Mag. 19, 94–95. doi:10.1109/MRA.2012.2192815

Sivak, M. & Schoettle, B. 2012, "Eco-driving: Strategic, tactical, and operational decisions of the driver that influence vehicle fuel economy", Transport Policy, vol. 22, pp. 96-99.

Skog, I. and Handel, P. (2014). Indirect Instantaneous Car-Fuel Consumption Measurements. IEEE Transactions on Instrumentation and Measurement, 63(12), pp.3190-3198.

Tao, S., Manolopoulos, V., Rodriguez, S. and Rusu, A. (2012). Real-Time Urban Traffic State Estimation with A-GPS Mobile Phones as Probes. Journal of Transportation Technologies, 02(01), pp.22-31.

Tostes, A.I.J., Duarte-Figueiredo, F.D.L.P., Assunção, R., Salles, J. & Loureiro, A.A.F. 2013, "From data to knowledge: City-wide traffic flows analysis and prediction using bing maps", Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.

Tse, R., Zhang, L.F., Lei, P., Pau, G., 2017a. Social Network Based Crowd Sensing for Intelligent Transportation and Climate Applications. Mob. Netw. Appl. doi:10.1007/s11036-017-0832-y

Tse, R., Zhang, L.F., Lei, P., Pau, G., 2017b. Crowd Sensing of Weather Conditions and Traffic Congestion Based on Data Mining in Social Networks, in: Gaggi, O., Manzoni, P., Palazzi, C., Bujari, A., Marquez-Barja, J.M. (Eds.), Smart Objects and Technologies for Social Good: Second International Conference, GOODTECHS 2016, Venice, Italy, November 30 – December 1, 2016, Proceedings. Springer International Publishing, Cham, pp. 353–361. doi:10.1007/978-3-319-61949-1_37

Vasconcelos, I., Vasconcelos, R.O., Olivieri, B., Roriz, M., Endler, M., Junior, M.C., 2017. Smartphone-based outlier detection: a complex event processing approach for driving behavior detection. J. Internet Serv. Appl. 8, 13. doi:10.1186/s13174-017-0065-0

Vlahogianni, E.I., 2015. Optimization of traffic forecasting: Intelligent surrogate modeling. Eng. Appl. Sci. Optim. OPT- - Profr. Matthew G Karlaftis Meml. Issue 55, 14–23. doi:10.1016/j.trc.2015.03.016

Vlahogianni, E.I., Barmpounakis, E.N., 2017. Driving analytics using smartphones: Algorithms, comparisons and challenges. Transp. Res. Part C Emerg. Technol. 79, 196–206. doi:10.1016/j.trc.2017.03.014

Vlahogianni, E.I., Karlaftis, M.G., Golias, J.C., 2014. Short-term traffic forecasting: Where we are and where we’re going. Spec. Issue Short-Term Traffic Flow Forecast. 43, 3–19. doi:10.1016/j.trc.2014.01.005

Wahlström, J., Skog, I., Händel, P., 2017. Smartphone-Based Vehicle Telematics: A Ten-Year Anniversary. IEEE Trans. Intell. Transp. Syst. PP, 1–24. doi:10.1109/TITS.2017.2680468

Wang, L., Groves, P.D., Ziebart, K.Z., 2013. Urban Positioning on a Smartphone: Real-time Shadow Matching using GNSS and 3D city models, in: Proceedings of the ION GNSS. Presented at the ION GNSS, Nashville, Tennessee.

Wang, L., Groves, P.D., Ziebart, M.K., 2012. Multi-Constellation GNSS Performance Evaluation for Urban Canyons Using Large Virtual Reality City Models. J. Navig. 65, 459–476. doi:10.1017/S0373463312000082

Wang, P., Wang, J., Chen, Y., Ni, G., 2013. Rapid processing of remote sensing images based on cloud computing. Spec. Sect. Adv. Cloud Monit. Syst. Fourth IEEE Int. Conf. E-Sci. 2011 — E-Sci. Appl. Tools Clust. Grid Cloud Comput. 29, 1963–1968. doi:10.1016/j.future.2013.05.002

Wang, S., Zhang, X., Cao, J., He, L., Stenneth, L., Yu, P.S., Li, Z., Huang, Z., 2017. Computing Urban Traffic Congestions by Incorporating Sparse GPS Probe Data and Social Media Data. ACM Trans Inf Syst 35, 40:1–40:30. doi:10.1145/3057281

White, C.E., Bernstein, D., Kornhauser, A.L., 2000. Some map matching algorithms for personal navigation assistants. Transp. Res. Part C Emerg. Technol. 8, 91–108. doi:10.1016/S0968-090X(00)00026-7

Woodard, D., Nogin, G., Koch, P., Racz, D., Goldszmidt, M., Horvitz, E., 2017. Predicting travel time reliability using mobile phone GPS data. Transp. Res. Part C Emerg. Technol. 75, 30–44. doi:10.1016/j.trc.2016.10.011

Xiao, G., Juan, Z., Zhang, C., 2015. Travel mode detection based on GPS track data and Bayesian networks. Comput. Environ. Urban Syst. 54, 14–22. doi:10.1016/j.compenvurbsys.2015.05.005

Xiao, L., Li, Y., Han, G., Dai, H., Poor, H.V., 2017. A Secure Mobile Crowdsensing Game with Deep Reinforcement Learning. IEEE Trans. Inf. Forensics Secur. PP, 1–1. doi:10.1109/TIFS.2017.2737968

Xu, T., Li, X., Claramunt, C., 2017. Trip-oriented travel time prediction (TOTTP) with historical vehicle trajectories. Front. Earth Sci. doi:10.1007/s11707-016-0634-8

Zamora, W., Calafate, C.T., Cano, J.-C., Manzoni, P., 2016. A Survey on Smartphone-Based Crowdsensing Solutions. Mob. Inf. Syst. 2016, 1–26. doi:10.1155/2016/9681842

Zeeman, A.S., Booysen, M.J., 2013. Combining speed and acceleration to detect reckless driving in the informal public transport industry, in: 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013). Presented at the 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013), pp. 756–761. doi:10.1109/ITSC.2013.6728322

Zhou, T., Cai, Z., Wu, K., Chen, Y., Xu, M., 2017. FIDC: A framework for improving data credibility in mobile crowdsensing. Comput. Netw. 120, 157–169. doi:10.1016/j.comnet.2017.04.015

Zandbergen, P.A. 2009, "Accuracy of iPhone locations: A comparison of assisted GPS, WiFi and cellular positioning", Transactions in GIS, vol. 13, no. SUPPL. 1, pp. 5-25.

Zirari, S., Canalda, P., Spies, F., 2010. WiFi GPS based combined positioning algorithm, in: 2010 IEEE International Conference on Wireless Communications, Networking and Information Security. Presented at the 2010 IEEE International Conference on Wireless Communications, Networking and Information Security, pp. 684–688. doi:10.1109/WCINS.2010.5544653