Journal of Network and Innovative Computing
ISSN 2160-2174 Volume 1 (2013) pp. 331-358

In-Vehicle Mobile Phone-Based Road Traffic flow Estimation: A Review

Ayalew Belay Habtie[1], Ajith Abraham[2] and Dida Midekso[3]

[1] Department of Computer Science, Addis Ababa University,
Addis Ababa, Ethiopia
ayalewbelay@gmail.com
[2] Machine Intelligence Research Labs (MIR Labs), WA, USA
ajith.abraham@ieee.org
[3] Department of Computer Science, Addis Ababa University,
Addis Ababa, Ethiopia
mideksod@yahoo.com

Abstract: **This paper presents a state-of-the-art review of the application of cellular network for estimation of real-time road traffic flow. Academic literature were analyzed and classified for in-vehicle mobile localization approaches (network-based, handset-based and hybrid) and urban road traffic flow estimation approaches (model based and data driven approaches). The findings of this review revealed that using the existing mobile cellular network infrastructure for road traffic management activity reduces deployment cost, can cover wide area of traffic flow detection and has also attracted great deal of attention in recent years.**

Keywords: **cellular network, positioning technology, road traffic management, road traffic flow estimation.**

1. Introduction

The number of motor vehicles is also increasing in different countries of the world. In general the world vehicle population reached 1.015 billion in 2010 [2] which is 3.6 % rise from 2009 and the average registered vehicle increase is high in low- and middle-income countries with an increasing rate of 7 % per year when compared to developed countries with a rate of 1 % per year [3].

The fact that traffic density is continuing to grow with traffic accident, congestion and environmental pollution problems, efficient road traffic flow policy and system which perform real-time load balancing resulting in more suitable transport service is needed. In relation to this, road traffic management systems are widely acknowledged as a means to optimize the utilization of existing transport infrastructure [4].These systems, which are developed using traffic surveillance technologies, enable to gather road traffic information, monitor and schedule the traffic flow, as well as guide and control the vehicles so as to improve the efficiency and safety of traffic flow and also to reduce pollution effect on the environment.

Existing road traffic management systems use fixed sensors, moving probes, mobiles and other location technologies for monitoring road traffic flow.

Fixed sensor-based traffic management systems refer to technologies where traffic data is gathered using detectors located along the roadside. Sensor-based traffic management systems are used for vehicle surveillance purpose. Indeed, such systems are able to collect and process vehicle count, speed, classification, occupancy and presence at real-time [6]. Sensor-based road traffic management systems could be either Intrusive or Non-Intrusive [7].

Intrusive traffic sensor technologies refer to those that require installation directly onto the pavements, in saw-cut, holes or tunnels under the pavement surface. Most conventional traffic surveillance systems use intrusive sensors, which include inductive loop detectors, micro-loop probes, pneumatic road tubes, piezoelectric cables and other weigh-in-motion sensors. For maximizing the benefits from all these surveillance technologies, there must be a large scale deployment of traffic controls on all major freeways and local streets. Yet this may not be viable or scalable as its installation and maintenance costs are high.

Non-Intrusive traffic sensor technologies do not need any installation on or under the pavement, so that the installation and repair of such a system can be done without disturbing the traffic. The detectors are usually setup on the roadside, or at an overhead position. Examples of this type of technology include microwave radar, infrared, Video Image Processing (VIP), ultrasonic and passive acoustic array. These surveillance technologies have limitations. For example, microwave radar cannot detect motionless vehicle unless an auxiliary device is used, performance of infrared system is greatly affected by the environment, as infrared energy is absorbed or scattered by atmospheric particles, such as fog, rain or snow and temperature change affects performance of Video Image Processing, ultrasonic and also acoustic array systems.

Both Intrusive and Non-Intrusive traffic surveillance technologies, which have expensive costs of implementation and maintenance, are installed at strategic locations along the highway to support road traffic monitoring and management activities. These technologies, even though matured with high potential and quality, the accuracy for travel time and area coverage as well as urban area precision is low [6].And because of their limited coverage, traffic data gathered using these technologies cannot produce reliable information about road traffic condition [8].

Mobile probe-based road traffic surveillance systems collect and process road traffic data by locating the vehicle via GPS or mobile phones over the entire road network. This basically means that every vehicle is equipped with mobile phone or GPS which acts as a sensor for the road network. Data such as car location, speed and direction of travel are sent anonymously to the central processing center. After being collected and extracted, useful information (e.g. status of traffic, alternative routes) can be redistributed to the customers on the road.

Mobile probe-based traffic management system is an alternative or a complement to source of high quality data to existing technologies. These monitoring systems improve safety, efficiency and reliability of the transportation system [6]. They are becoming crucial in the development of new Intelligent Transportation Systems (ITS).

Floating vehicle technologies are one category in mobile probe-based traffic monitoring systems that are based on either GPS or Cellular Network. GPS equipped vehicle can obtain its own accurate and detailed trajectory. The vehicle location precision is relatively high, typically less than 30m [6].GPS-based traffic management systems are vital for Intelligent Transport system that guarantee safety and improve traffic management as it provide high location accuracy for broad range of traffic data estimation. Currently, GPS probe data are widely used as a source of real-time information by many service providers but it suffers from a limited number of vehicles equipped with GPS and high equipment costs compared to cellular network-based traffic management system [9]. Hence, traffic data from GPS equipped vehicle has limited sample size and can't be representative for the entire population when compared with cellular-network based solution. Moreover, benefits of GPS could be limited and backup could be needed where location information is needed due to obscure view to satellites or degraded accuracy due to multipath [10].

Millions of mobile devices are held by vehicle drivers and it may be worth using mobile phones as anonymous traffic probes. Mobile phones are means to collect and process traffic data in cellular network-based traffic control systems and need to be turned on, but not necessarily in use. This approach is particularly well adapted to deliver relatively accurate information in urban areas where traffic data are most needed due to the lower distance between antennas [11].

Contrary to stationary traffic detectors and GPS-based systems, in cellular network-based traffic management system, no special device/hardware is necessary in cars and no specific infrastructure is to be built along the road. It is therefore less expensive than conventional detectors and offers larger coverage capabilities. Traffic data are obtained continuously instead of isolated point data. It is faster to set up, easier to install, and needs less maintenance. In this paper we attempt to provide a comprehensive review and current state-of-the-art of using mobile cellular network for road traffic flow assessment together with mobile positioning principles.

The rest of this paper is organized as follows. Section 2. discussed a comprehensive review on existing knowledge for in-vehicle mobile positioning techniques and road traffic flow estimation approaches. Section 3 presents the methodology that has been used and the classification is illustrated. Finally, conclusion and directions of future research are discussed in Section 4.

2. Literature Review

Mobile positioning has become a remarkable technology because of its commercial potential, increased subscriber safety and services envisaged under Intelligent Transport System. The driving force for mobile positioning was initiated by the U.S. FCC (Federal Communication Commission) in the case of emergency calls. The calling party of all emergency calls (911) in the United States should be located with a defined degree of accuracy [13], [14]. Other countries use similar system but define different numbers such as 110 for China, 999 for UK and 17 for France [14]. In Europe; the European Community defines positioning performance requirements for emergency location to their E-112 location systems [15], as specified in Table 2. In contrast, vehicle positioning requires greater accuracy. Location technologies are increasingly designed to meet the requirements for certain location-based services (LBS), rather than simply to meet the mandatory regulations (as per Tables 1 and 2). Table 3 lists some specific LBS and their expected accuracy ranges [16].

Table 1. Accuracy Requirements from FCC[14]

Solution	67% of calls	95% of calls
Handset-Based	50 meters	150 meters
Network-Based	100 meters	300 meters

Table 2. E-112 Accuracy Guideline[15]

Urban	Suburban	Rural	Crossroads
50 meters	50 meters	100 meters	<100 meters

Table 3. LBS Position Accuracy[16]

Service Type	Accuracy Rage
Fleet Management	125m-Cell ID
Network Planning	10m-Cell ID
Asset Management	10m-125m
Person Tracking	10m-125m
Navigation and Route Guidance	10m-125m
Traffic Congestion Reporting	10m-40m

Vehicle positioning requires high resolution and accuracy for proper navigation. The positioning technology used should have the ability to determine the vehicle location within 20 meters of the actual location for about 90% of the travel time [12] which is in the accuracy range of 10 m - 40 m for Traffic Congestion Reporting in Table 3 as Traffic Congestion Reporting is standardized location based service type in 3rd Generation Partnership Project (3GPP) within the category of Traffic monitoring [16]. Generally, accuracy, precision and coverage are the three important

performance measures for positioning technologies but positioning accuracy is a critical factor when selecting a positioning technology for different services [17]. To evaluate performance of position location methods, different standards were proposed. One of them is Root-Mean-Square (RMS) and it is specified for two dimensions which is composed of standard deviation of two one-dimension axes (σN for Northing axis and σE for Easing axis) spanning two-dimensional plane[18]. Depending on the distribution of the error, the position samples may center in a confidence circle or ellipse around the true positions as illustrated in Figures 1 and 2.
When the error distribution is the same in both dimensions, the position samples center in a confidence circle (see Figure 2) and σN= σE. The standard deviation is defined as:

$$\sigma D2 = \sqrt{2(\delta_N)^2} = \sqrt{2(\delta_E)^2} \quad (1)$$

When the error distribution in the two-dimensions differ, the positing samples center around a true position of confidence ellipse and it is approximated as:

$$\sigma D2 = \tfrac{1}{2} (\sigma N + \sigma E) \quad (2)$$

Where σN is standard deviation for Northing axis and σE for Easing axis. The Root Mean Square Error (RMSE) is also used to measure the aggregate error on position estimate [19] and defined as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{K=1}^{N} [x_{Measured}(K) - x_{True}]^2} \quad (3)$$

Where N is the total number of trials and X $_{Measured}$ is the position estimates in the Kth trial.
The other measure of accuracy is the comparison of the Mean-Square-Error (MSE) or root-mean-square (rms) position error with the Cramer-Rao Lower Bound (CRLB)[20]. For a location in two-dimension, the MSE position estimate is given by:

$$MSE = E\left[(x - x')^2 + (y - y')^2 \right] \quad (4)$$

Where (x, y) is coordinate of a target and (x', y') is the estimated position and E represents the expected value of the squared difference between an estimate and the actual observed value of the parameter.
Geometric Dilution of Precision (GDOP) is used to measure effects of base station Configuration on location estimation. GDOP is defined as the ratio of root-mean-square (rms) position error to root-mean-square ranging error [20] and for unbiased error it is given by:

$$GDOP = \frac{\sqrt{E[(x - x')^2 + (y - y')^2]}}{\delta_r} \quad (5)$$

where δ_r represents the fundamental ranging error of the positioning technique.

A. Basic Mobile Positioning Techniques

There are six different positioning methods but only two of them are important for mobile positioning in cellular network [18]. These positioning methods are proximity sensing and lateration.

1. Proximity Sensing

It is the most widespread positioning method used to obtain location of mobile device based on limited coverage of radio signal The location of a mobile device is derived from the coordinates of the base station that either receives the pilot signals from a terminal on the uplink or whose pilot signals are received by the terminal on the downlink channel. Locating the mobile device is done during ongoing connection or if the mobile device is idle. In the former case, the network simply adopts the coordinates (X_1, Y_1) of the base station that currently serves the terminal. If the terminal is idle, the mobile device listens to the broadcast transmissions of nearby base stations and derives a position fix by contacting a remote database that performs a mapping from cell identifiers to base station coordinates. The base station that sends or receives signal is assumed to be near the location of the mobile device and the expected deviation error is dependent on the radius of sensing area [18]. It is illustrated in Figure.1.

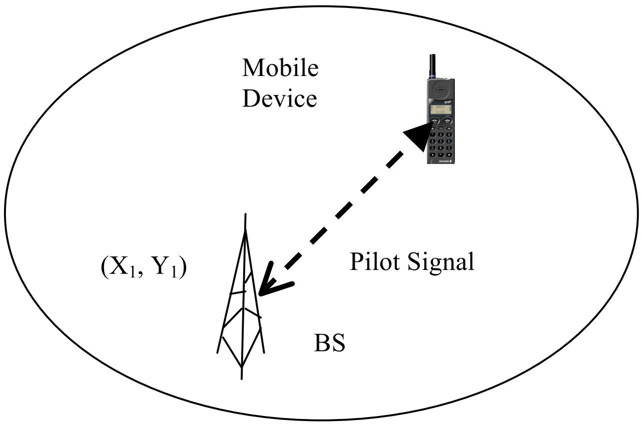


Figure 1. Proximity Sensing Illustration

2. Lateration

Lateration is a mobile positioning method that tries to determine location from multiple distance measurements [21]. In this method mobile device position is determined either from absolute distance or distance differences from at least three base stations. If positioning is based on absolute distance measurements, the position fix is calculated by circular lateration, while distance differences form the basis for hyperbolic lateration.

Circular lateration uses the assumption that the distances r_i between the mobile device and number of base stations are known [18]. For unambiguous positioning of mobile device at least three base stations with known coordinates (X_i, Y_i) are required. The unknown mobile device position (X, Y) is the intersection of the three circles as it is depicted in Figure 2 and using the Pythagoras theorem its location is given as:

$$r_i = \sqrt{(X_i - X)^2 + (Y_i - Y)^2} \quad (6)$$

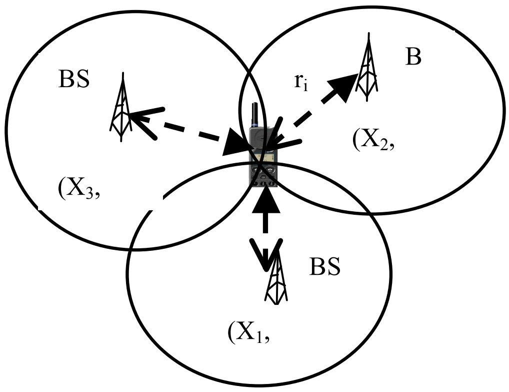


Figure 2. Circular Lateration illustration

Due to refraction, inaccurate clock synchronization and multipath propagation, the measured distance d_i may have a deviation error ε_i from the actual distance r_i. Hence, the circles will not have intersection point (X, Y) rather becomes error margin as shown in Figure 3.

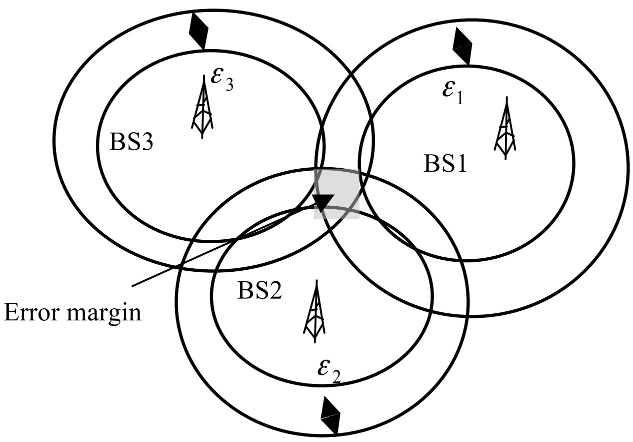


Figure 3. Error Margin of Circular Lateration

In hyperbolic lateration method of mobile device positioning, the location of the mobile device is determine by the distance difference ($r_i - r_j$) instead of the absolute distance r_i. A Hyperbola is a set of points where the distance from two fixed points is constant [18]. Considering two base stations with known coordinate forms hyperbolic curves and their intersection can help to determine a fixed point. To determine position of mobile device three base stations are required and its location is illustrated in Figure 4. Like circular lateration, hyperbolic lateration has an error potential because of inaccuracies of range difference measurements. The error potential of two intersecting hyperbolas is depicted in Figure 5. Therefore, a least square fit can be used again to approximate a solution.

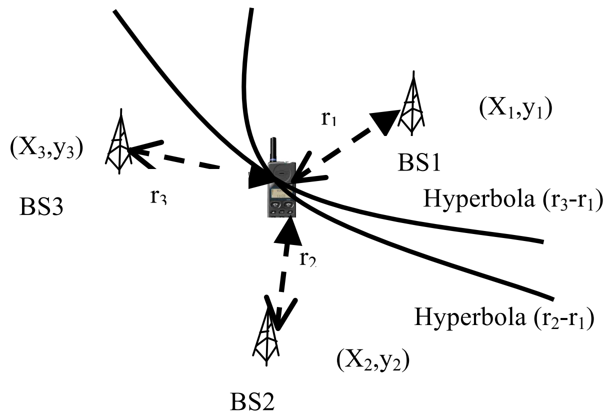


Figure 4. Hyperbolic Lateration

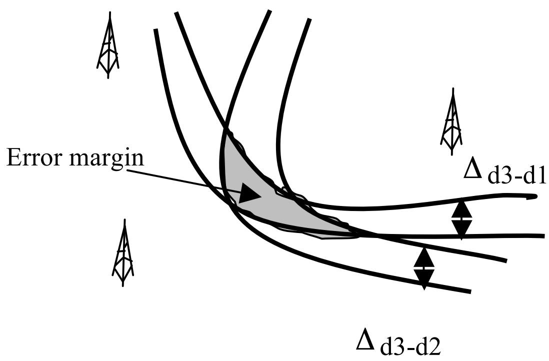


Figure 5. Error margin for Hyperbolic lateration

B. Standardization of Mobile Phone positioning

The acceptance and success of services developed using position technologies is essentially based on the availability of appropriate standards. Standards guarantee a seamless interworking between equipment and software originating from different sources and in this way enable the use of services that are technically independent of a certain operator or provider.

The 3rd Generation Partnership Project (3GPP) is an international collaboration of several national standards bodies and focuses on the production of technical recommendations and reports for wideband code-division multiple access (W-CDMA) and Global System for Mobile Communication (GSM) systems while 3GPP2 is focusing on CDMA2000 and CDMA One system.

Location Service (LCS) is primarily concerned in delivery of location data and it is very important for building Location-Based Services [18]. According to 3GPP, LCS covers several generations of radio access networks (RAN) like GERAN (GSM, EDGE RAN), UTRAN (UMTS

Terrestrial RAN) and E-UTRAN (Evolved Universal Terrestrial RAN). EDGE (Enhanced Data rate for Global Evolution) is an evolution with respect to the 2G system .i.e., GSM. UMTS (Universal Mobile Telecommunication System) is a 3G system commonly named WCDMA. E-UTRAN refers to the 4G system which is LTE (Long Term Evolution).

3GPP specifications are continuously enhanced with new features and these enhancements are structured and coordinated based on releases. For example, specification TS 22.071 [16] provides overall descriptions and requirements of LCS. Specification TS 23.271 [22] provides LCs architecture and message flow. This specification, unlike TS 22.071 that describes services with respect to the subscribers' point of view, presents the service realization and also to operators and providers point of view.

While determining position location particularly in GSM and UMTS network three basic activates are performed. The first one is location preparation where determination of position method used and checking privacy policy is done and the second one is establishing position measurement. In this step, components like SLMC, LMU and UE/MS exchange measurement data. After successful measurement position location is calculated either at the terminal or in the network and resources involved during the process is released. The following subsection illustrates the standardized position methods in GSM and UMTS networks.

1. Standard Mobile Positioning in GSM Networks

For GERAN (GSM/EDGE Radio Access Network), different mobile positioning methods are developed and each differs in degree of accuracy and complexity of control mechanism in the network and in the MS/UE. 3GPP TS 43.059 [23] specifies four positioning methods which are supported in GSM/EDGE RAN.

Time Advance (Cell-ID in combination with Timing Advance): Cell-ID is based on proximity sensing, that is, the position of the target MS is derived from the coordinates of the serving base station. To achieve position fixes of higher accuracies, Cell-ID is combined with timing advance value. Timing Advance (TA) Value corresponds to the time a signal takes from MS to serving base station. In this method, the Cell ID of the corresponding serving base station together with the
TA value is returned.

Enhanced Observed Time Difference (E-OTD) positioning mechanism: This method is based on hyperbolic lateration (trilateration) and is applied in the downlink channel. The E-OTD method is based on measurements in the MS of the Enhanced Observed Time Difference of arrival of nearby pairs of BTSs. For E-OTD to work properly additional software and hardware need to be added in the network [14].

Global Navigation Satellite System (GNSS) based positioning mechanism: Global Navigation Satellite System (GNSS) are satellite systems like Galileo that are set up for positioning purposes [23]. The MS must be equipped with a GPS receiver and are supplied by additional assistance data from the network, which allows to reduce the acquisition time and to increase the accuracy of position fixes. The MS with GNSS measurement capability may operate in an autonomous mode or in an assisted mode. In the autonomous mode, MS determines its position based on signals received from GNSS without assistance from network. In the assisted mode, MS receives assistance data from network.

Uplink Time Difference of Arrival (U-TDOA) positioning mechanism: This method is also based on hyperbolic lateration, but is applied in the uplink. It is based on network measurements of the Time Of Arrival (TOA) of a known signal sent from the mobile station and received at three or more BTSs. This method will work with existing mobile stations without any modification because the position calculation is done by the network not at the handset like E-OTD.

2. Standard Mobile Positioning in UMTS Networks

3GPP TS 25.305 (Technical Specification Stage 2 functional specification of User Equipment
(UE) positioning in UTRAN) [24] provides methods to support the calculation of the user Equipment (UE) position. Four standard positioning methods are supported in UMTS Terrestrial RAN.

Cell-Based Method: In UMTS, the Cell-Based method estimates the position of a UE based on the nearby base station that is Node B. If required, position data can be refined by taking into account the distance between UE and base station, which can be derived from round-trip-time (RTT), the Angle Of Arrival (AOA) of signals from the terminal at the base station, or both of them.

Observed Time Difference of Arrival with idle period downlink (OTDOA-IPDL): This method is basically the UTRAN counterpart of E-OTD in GSM and follows the same principles, that is, The UE's position is determined by hyperbolas lateration based on at least two pairs of Node Bs. However, UEs may have difficulty hearing a sufficient number of cells needed for TDOA calculations. One solution, specified by 3GPP for this problem, is an idle period downlink (IPDL) where the serving Node B introduces idle periods in the downlink to improve the hearability of weaker neighboring Node Bs.

Network-assisted GNSS (A-GNSS): As in GSM, a network-assisted GNSS method is also standardized in UTRAN. In particular, 3GPP TS 25.305 specified network-assisted GPS (A-GPS) in detail as a separated clause in the standard. The two A-GPS methods specified in UTRAN are UE-based and UE-assisted. Computation of the position can either be performed in UTRAN for UE-assisted or in the UE for UE-based. In UE-based, the UE employs GPS receiver with reduced complexity, whereas in UE-assisted; a full GPS receiver is required in the UE.

Uplink-Time Difference of Arrival (U-TDOA): The U-TDOA positioning method in UMTS is network-based and it is basically the same as U-TDOA in GSM. The difference between U-TDOA and OTDOA lies whether the measurement is done by the network or by the UE. In UTRAN, the U-TDOA shows significant advantage over its handset-based counterpart [25]. In this method no need to modify the neither UE nor Node B. Network management becomes easier, as it is less complex to upgrade the software in network entities than it is to upgrade millions of UE.

3. Standard Mobile Positioning in GSM Networks

3GPP TS 36.305 (the functional description of UE positioning in E-UTRAN)[26] describes the E-UTRAN (Evolved UTRAN) UE positioning Architecture, functional entities, operations to support positioning methods and the position estimation is made by UE or the Enhanced Serving Mobile Location Centre (E-SMLC). In the latest (Release 11), four UE position standards are supported for E-UTRAN access.

Network-assisted GNSS Methods: These methods make use of UEs that are equipped with radio receivers capable of receiving GNSS signals. As it is specified in detail in a separate clause in the standard, there are two Network-assisted GNSS Methods: UE-Assisted and UE-Based. In UE-Assisted, the UE performs GNSS measurements and sends these measurements to the E-SMLC where the position calculation takes place and in UE-Based, the UE performs GNSS measurements and calculates its own location, possibly using additional measurements from other (non GNSS) sources.

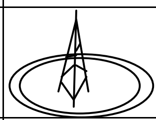
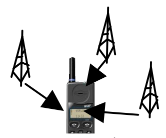
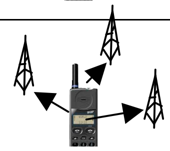
Downlink positioning: The downlink (OTDOA) positioning method makes use of the measured timing of downlink signals received from multiple eNode Bs at the UE. The UE measures the timing of the received signals using assistance data received from the positioning server, and the resulting measurements are used to locate the UE in relation to the neighboring eNode Bs. eNode B is a network element of E-UTRAN that may provide measurement results for position estimation and makes measurements of radio signals for a target UE and communicates these measurements to an E-SMLC.

Enhanced Cell ID Methods: In E-UTRAN, Enhanced Cell ID method, the position of an UE is estimated with the knowledge of its serving eNode B and cell. To know the serving eNode B and the cell Paging, tracking area update, and other methods are used. Detail operation on Enhanced Cell ID is described in a separate clause in the standard.

Uplink positioning: The uplink (UTDOA) positioning method makes use of the measured timing at multiple LMUs of uplink signals transmitted from UE. The LMU measures the timing of the received signals using assistance data received from the positioning server, and the resulting measurements are used to estimate the location of the UE. Hybrid positioning using multiple methods from the above positioning methods is also described in 3GPP TS 36.305 specification standard.

In general, the standard mobile positioning methods in GSM, UMTS and LTE can fall in to four classes: Cell area coverage based, downlink observed time difference, uplink time difference of arrival and network assisted GNSS. Table4 gives summary of the different techniques with respect to each generation of networks.

Table 4. Summary of standard location methods in cellular network generations

Mobile Positioning Method	Diagram demonstrating the method	Standard Mobile Positioning Technique	Generation of Cellular Network
Cell Area Coverage Based		CID-TA	GSM
		CID-RTT	UMTS
		E-CID	LTE
Downlink Observed Time Difference		E-OTD	GSM
		OTDOA-IPDL	UMTS
		Downlink	LTE
Uplink Time Difference of Arrival		U-TDOA	GSM
			UMTS
			LTE
Network assisted GNSS		A-GPS	GSM
			UMTS
			LTE

C. Classification of Mobile Positioning Technologies

Different types of location-based services require different position technologies based on position accuracy. Each positioning technology provides location information in its unique way. As highlighted in 3GPP specifications, each positioning technology has its own positioning logic. Despite their numerous variations, these standardized methods can be systematically classified. According to the FCC requirements[14], positioning technologies are classified into two: network-based and handset-based (terminal-based) mobile positioning technology.

There is also another way to classify positioning technologies: self-positioning and remote positioning technology. But Self-positioning is generally synonymous with handset-based and remote positioning with network-based[21].

1. *Network-Based Mobile Positioning Technologies*

This category is referred as "Network-based" because the mobile network together with the Network-based positioning determination equipment is used to position the mobile device. Network-based positioning method has advantages that all legacy UEs can receive location service without upgrading. Because the network has more computing power, it can help for positioning when difficult using Handset-based method. It also reduces power consumption of the UE. The system can initiate target positioning and tracking without intervention or action by the target and the network operator could use the information for position based tariffs, generate and store statistics gross movement of the customers for network planning, feed into systems detecting traffic congestion and provide the mobile user with variety of position-based services (e.g. route guidance). However, Network-based positioning methods not only use network resources but also involve changes in the infrastructure as described in Table 5.

Table 5. Infrastructure change requirements in Network-based positioning standards.

Generation of Cellular Network	Network-based mobile positioning method	Infrastructure change requirement	
		Network	Handset
GSM (2G)	CID-TA	Software	No
	U-TDOA	Hardware	No
UMTS (3G)	CID-RTT	Software	No
	U-TDOA	Hardware	No
LTE (4G)	E-CID	Software	No
	U-TDOA	Hardware	No

There are so many performance metrics to evaluate different positioning technologies. Among those metrics accuracy, latency, availability, reliability and applicability are of major importance [27]. Accuracy of a positioning technology refers to how close the location measurement is with respect to the UE be located. And in network-based positioning accuracy must be 100 m for 67% of all calls and 300m for 95% of all calls [14]. Availability is related to environmental factors affecting positioning and it is represented based on classes like Remote, Rural, Suburban, Urban, Indoor and Underground [27]. The accuracy also is defined based on these classifications for E-112 guideline [15] and recommended to be applied for vehicle positioning [21], [28]. Table 6 presents accuracy of Network-based positioning methods in Urban, Suburban and Rural areas.

Table 6. Comparison of Network-based positioning methods using Accuracy and availability.

Positioning Method	Accuracy vs. Availability		
	Urban	Suburban	Rural
CID-RTT	50m-550m	250m-2.5km	250m-35km
U-TDOA	40m-50m	40m-50m	50m-120m

As evident from Table 6, U-TDOA is better to approach the Traffic monitoring accuracy range 10m-40m. Reliability is the ratio of successful positioning attempt out of all attempts performed. Latency measures the time that the position measurement takes from power-up until it is acquired.

Applicability refers to physical limitations and requirements in relation to the use and implantation of the Network-based positioning method. Some of the issues affecting positioning include power consumption, hardware and software size, processing load, cost and standardization. Table 7 depicts these evaluation metrics in relation to Network-based positioning methods. From Table 7, one can see that CID-RTT Network-based positioning method provides very good reliability, minimum latency of measurement and easy to apply. But its position accuracy is not within the requirement.

Table 7. Comparison of Network-based positioning methods with respect to reliability, latency and applicability.

Positioning Method	Reliability	Latency	Applicability
CID-RTT	High	1-5sec	high
U-TDOA	Medium	<10sec	low

2. Handset-Based Mobile Positioning Technologies

This category is referred as “Handset-Based” because the handset itself is the primary means of positioning the user. Sometimes the network is used to provide assistance for acquiring the UE or performing position estimation. In other words, in a handset-based location system, any location measurement is made in the handset. Handset-based positioning systems can be used with cellular networks that are not designed for location service and even with low capacity because handset-based positioning technologies don’t use facilities and resources of the network. Moreover, roaming handsets can be used in position measurement activity. Since the handset is not limited on the number of measurements it can take, to improve position accuracy more measurements can be taken. For some situations this positioning method is more secured, as the location information is not available in the network. But Handset-based positioning method demands the UE with high power consumption. To perform location estimation, special software, and often hardware is incorporated in the handset as well as in the network [21].

Table 8. Resource requirements in Handset-based positioning Standards

Generation of Cellular Network	Handset-based mobile positioning method	Resource requirement	
		Network	Handset
GSM (2G)	E-OTD	Hardware	Software
	A-GNSS	Hardware	Hardware & Software
UMTS (3G)	OTDOA-IPDL	Hardware	Software
	A-GPS	Hardware	Hardware & Software
LTE (4G)	A-GNSS	Hardware	Hardware & Software
	Downlink	Hardware	Software

Table 8 shows the different Handset-based positioning methods together with the resource requirements across the different cellular network generations. The performance metrics used to evaluate Handset-based methods include accuracy, latency, availability, reliability and applicability are of major importance[27].

The performance metrics used to evaluate Handset-based methods include accuracy, latency, availability, reliability and applicability are of major importance[27].

The position accuracy of Handset-based positioning methods as specified in FCC must be 50m for 67% of the measurements and 50m for 90% of the calls [14]. Table 9 presents accuracy of Handset-based positioning methods in Urban, Suburban and Rural areas as classified in [15], [27].

Table 9. Comparison of Handset-based positioning methods using Accuracy and availability.

Positioning Method	Accuracy vs. Availability		
	Urban	Suburban	Rural
OTDOA-IPDL	50m-3000m	50m-250m	50m-150m
A-GPS	10m	10m-20m	10m

As it can be seen from the table 9, A-GPS has very good positioning accuracy. In relation to reliability, latency and applicability of Handset-based positioning methods, Table 10 shows that A-GPS has very low latency and moderately reliable as well as applicable.

Table 10. Comparison of Handset-based positioning methods with respect to reliability, latency and applicability.

Positioning Method	Reliability	Latency	Applicability
OTDOA-IPDL	medium	<10sec	medium
A-GPS	medium	1-10sec	medium

III. Hybrid Mobile Positioning Technologies

In hybrid positioning system, both the handset and the network are involved in the positioning function. In 3GPP, it is defined as the concurrent use of one Network-based positioning method with single Handset-based positioning technology to provide single location request service [29]. This combination enables to supplement and complement the limitations of one mobile positioning technology by capability of another. So, hybrid-positioning methods optimize accuracy, coverage, and availability and also decrease latency of location delivery as it is shown is Figure 6.

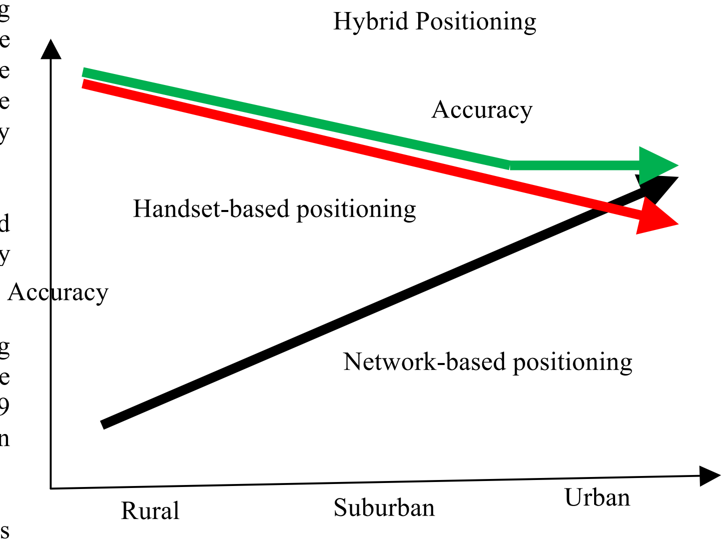


Figure 6. Position accuracy comparisons for different Mobile positioning Categories [30].

There is no literature that identifies positioning method that is perfectly suitable for vehicle positioning. But UTRAN supports a hybrid positioning solution from location technologies using separate resources. According to Chew [17], a framework of hierarchical integration of positioning technologies to support delivery of optimal position location is proposed. The interoperability of the integrated technologies is shown using dependency relationship as it is shown in Figure 7.

In a hybrid positioning method, cellular network operators emphasize the implementation of at least one Network-based positioning method [18], [21] due to the fact that legacy handsets are used in the positioning activity and in the cellular network the infrastructure migration is smooth.

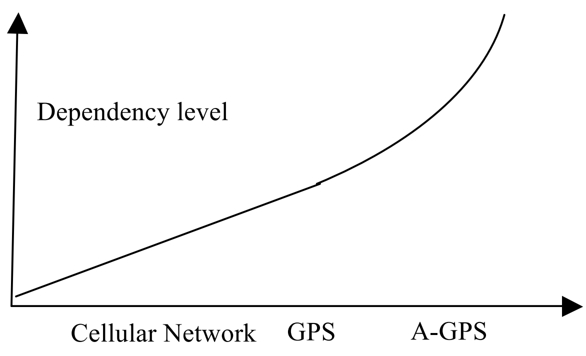


Figure 7. Dependency Level of positioning technologies

As evident from Figure 7, cellular network positioning methods (Handset-based and Network-based) are with the lowest level of dependency as the ability to locate position and area coverage is high. But A-GPS, because it needs resources like the network as well as server to compute position, its dependency level is high.

D. Road Traffic Condition Estimation Approaches

Real-time road traffic information is important for road traffic management activities like incident detection, traffic monitoring and so on. The traffic data can be gathered from several sources like loop detectors, microwave radars and more recently from mobile users [31]. Nowadays, road traffic information estimation from cellular networks has received much attention because of the widespread of the cellular network, its low cost, all-weather traffic information collection and with large number of mobiles to be used as location probes covering the whole road network. In order to estimate road traffic information from cellular network, the basic steps like location data collection, cell phone mobility classification, map matching, route determination and road traffic condition estimation are included [32].

1. Location Data Collection

This phase involves how to gather relevant vehicle location data from cellular network. As it is discussed in section 2.1.4, location data can be collected from the cellular network using handset-based positioning method also named as active monitoring approach, Network-based method in some literatures also called passive monitoring and hybrid-based positioning method. The hybrid-based positioning method, which is discussed in detail in section 4C and also the suggestion of recent commercial systems [33]-[34] provides good positioning accuracy and coverage as the advantage of one positioning method improves the limitation of the other

2. Cell Phone Mobility Classification

While moving vehicle location data is collected from cellular network using one of the positioning technology discussed in section 4, the data could be from various types of mobile carriers like mobile phones in moving vehicles, carried by pedestrians, held by bicycle and motor cycle riders, stationary mobile phones etc. As the objective is to estimate travel times of road users, discrimination between mobile phones in moving vehicles and other phones is necessary.

In relation to this, mobility characteristic like speed, directivity, update interval and erraticity of mobile devices are also used for mobile device classification [35]. If the necessary information on active/switched on mobile phone like date, time, Cell Identification (Cell-ID) and its location coordinates is collected, fusion of speed, direction and location information enable to classify mobile phones in moving vehicles and others [36].

Speed

Speed is used to classify the type of mobility. In consecutive time interval, if a mobile phone traveled with a speed of *v* larger than some specified threshold repeatedly, the mobile phone is in a moving vehicle and it is defined as [35]:

$$v_i(t_n) = \frac{\sqrt{(y_i(t_n) - y_i(t_{n-1}))^2 + (x_i(t_n) - x_i(t_{n-1}))^2}}{t_n - t_{n-1}} \tag{9}$$

Where $v_i(t_n)$ is the speed of the cell phone between t_n and t_{n-1} with location (x_i, y_i) at time t_{n-1} and t_n.
The work of Gundlegard and Karlsson [37], for example, discussed that speed can be used to filter stationary and pedestrians mobile phones. If a mobile phone has speed below 6km/hr it can be ignored as it will not be in moving vehicle. But during congestion when vehicles are travelling at lower speed from the threshold, mobile devices that are registered recently for higher speed though the current speed is lower than the threshold are considered to be valid probes.

Directivity

This represents the amount of angular change in the direction of the movement of a mobile device compared to a previous measurement. Pedestrians compared to vehicular mobile device present large directional changes. Directivity is measured using a specified time scale T. The direction of movement θ_n at time (t, t + T) is defined as [35]:

$$\theta_n = \arctan\frac{y_{n+1} - y_n}{x_{n+1} - x_n} = \arctan\frac{dy_{n,n+1}}{dx_{n,n+!}} \tag{10}$$

And also at the time interval (t +T, t+2T) the direction of movement is given as:

$$\theta_{n+1} = \arctan\frac{y_{n+2} - y_{n+1}}{x_{n+2} - x_{n+1}} = \arctan\frac{dy_{n+1,n+2}}{dx_{n+!,n+2}} \tag{11}$$

Hence, a directivity element is equal to $\beta_n = \theta_{n+1} - \theta_n$ at time scale *T*.
Computation of θ_i depends on at which quadrant of the Cartesian coordinate system the location coordinates fall, and the movement is directed. The directive vector $\beta(T, N) = (..\beta_{n,}\beta_{n+1,}\beta_{n+2,}..)$ includes the last *N* directivity measurements (*T*,*N*) is expected to be stored by the network service provider. Fast moving vehicles are mostly with smaller directivity [36].

Update interval

This is the time interval between two consecutive location updates of a particular mobile device. The location updates can be done centrally by the network requiring the mobile device to update its location. On the other hand, there are suggestions in the literature [38] that, to alleviate the signaling load on the network due to periodic updates, the mobile device updates its location whenever it crosses a boundary of a pre-determined area (e.g., circular, elliptic, etc.) centered at the coordinate of its last location update. Because the location of mobile devices is updated whenever the mobile devices cross the boundary of the cell, frequency of location update is a function of the radius of the cell. Hence, slow moving mobile devices like pedestrians or bicycle riders update their location less often than fast moving mobile devices like vehicles.

Erraticity

Assume that a circle of radius **r** defines the region for the location updates. When a mobile device traverses a distance **d** from the time of a location update (t_O) at position O to the next one (t_A) at position A, the corresponding erraticity within time frame [t_O, t_A] is denoted as E(t_O ,t_A) , and analytically represented as [35]:

$$E(t_O, t_A) = (1 - \frac{r}{d}) \quad (12)$$

Erraticity has no units, and takes values from [0,1] where 1 indicates the highest level of randomness and 0 the lowest level (e.g., movement with no directional change between two consecutive location updates). The comparison of the erraticity levels is made within each corresponding location updates interval and it is used in conjunction with the Update Interval. Other approaches like location registration scheme [39] and Naïve Bayes model [40] are also used to discriminate mobile phones in moving vehicles from others.

3. Map Matching

The data collected from cellular network cover many roads and also most measurements suffer from non-line of sight error as well as sampling error which makes the vehicles position is unreliable. Hence, projection of position/velocity estimates on to road links is needed using map matching algorithms. Map matching is the process of determining vehicle's location on the road segment, using the geographic coordinates obtained by mobile positioning technology and digital road map [41]. Map matching and route determination are often done together. Map matching algorithms are used to accurately locate a vehicle on a road map. The inputs to the algorithms come from mobile positioning technology and supplement this with data from a high resolution spatial road network map to provide an enhanced positioning output [42]. Map matching enables to identify physical location of a vehicle and also improves positioning accuracy depending on the quality of the spatial road network data [43]. Moreover, depending on the positioning technology used to collect vehicle location, the map matching approach differs [37]. There are different map matching algorithms produced and published in the literature. Most of these algorithms are designed for in-vehicle navigation systems equipped with GPS, Differential GPS and Dead Reckoning (DR). Based on the approaches, the algorithms can be categorized into four groups: geometric, topological, probabilistic and advanced map matching techniques.

Geometric map matching algorithms

Geometric map matching algorithms use the geometric information of the digital road network considering the shape of the links but do not consider the way links are connected to each other [44]. The most commonly used geometric map matching approach is based on a simple search concept. In this approach, each positioning point matches to the closest 'node' or 'shape point' in the road network and it is named point-to-point matching [45]. In point-to-point matching, each measured vehicle location point is matched to the nearest node or shape point in the digital road network map as shown in Figure 8.

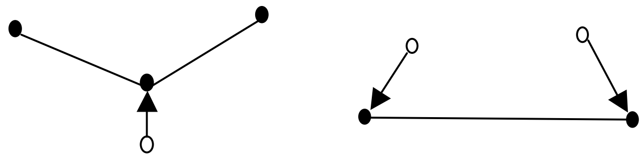


Figure 8. Point-to-Point map matching approach

To identify the closest node (or shape point) from a given point in the road network, Euclidian distance measurement is used. The measure of the Euclidean distance between two points x and y in $\mathbf{R^2}$ is given by:

$$\|x\text{-}y\| = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \quad (13)$$

This method is easy to implement, although it is very sensitive to the way in which the network was digitized as it may lead to errors [46].

Point-to-Curve matching is another geometric map matching approach where the measured vehicle location is matched on to the closest road network curve [47, 48]. Each of the curves comprises line segments which are piecewise linear. Distance is calculated from the position fix to each of the line segments. The line segment which gives the minimum Euclidean distance is selected as the one on which the vehicle is apparently travelling. The minimum Euclidean distance from measured location c to line A containing points a and b which is denoted as $\{\lambda a + (1\text{-}\lambda)b , \lambda \in R\}$ is given by:

$$d(c,A) = \sqrt{\frac{\{(a_2 - b_2)c_1 + (b_1 - a_1)c_2 + (a_1 b_2 - b_1 a_2)\}^2}{(a_2 - b_2)^2 + (b_1 - a_1)^2}} \quad (14)$$

Accordingly, if the minimum distance of point c is on a line segment between points a and b of the curve, it becomes the matched point, otherwise if the perpendicular distance between point c and line A intersect outside the lines segment, minimum distance from points c and a or from points c and b is selected as matched point (see Figure 9).

Figure 9. Point-to-Curve map matching approach

Although this approach gives better results than point-to-point matching, it has several shortcomings that make it inappropriate in practice. For example, it gives very unstable results in urban networks due to the high road density. Moreover, the closest link may not always be the correct link [45].

The other geometric map matching approach is curve-to-Curve matching. In this approaach, more than one measured location is attributed to contineous road segments.Several location points are connected to form piecewise linear curve. Another piecewise linear curve is constructed using the vehicles trajectory and then the distance between the previous curve and the curve corresponding to the road network is determined. The road arc which is closest to the curve formed from positioning points is taken as the one on which the vehicle is apparently travelling. This approach is quite sensitive to outliers and depends on point-to-point matching, with the consequence of sometimes giving unexpected results [42, 45]. The distance between piecewise curves A and B is defined as:

$$\|A-B\|_2 = \int^1 \| a(t) - b(t) \| \, dt \quad (15)$$

Topological map matching algorithms

These map matching algorithms make use of the geometry of the links as well as the connectivity and contiguity of the links [44, 49]. Topological map matching algorithms utilize both geometrical and topological data to make matching decision. Topological map matching algorithms are simple, easy and quick and can be implemented in real-time [50].

Probabilistic map matching algorithms

Topological map matching algorithm starts with nodal matching to identify the correct link among the links connected to the node closest to the estimated vehicle location. For complex urban road networks with high-resolution digital maps, topological map matching algorithm is not helpful. Instead of using the links connected to the closest node, the map-matching algorithm should take all links as candidate links that fall within an error ellipse around a position fix. The dimensions of the error ellipse are chosen based on the error variance-covariance matrix associated with the location estimation technology. The size of the error ellipse normally depends on the probability (95% or 99%) that the ellipse contains a true link [42].

Probabilistic map matching method is also discussed in [46] depending on GPS sensor for vehicle location and suggested that the error region can be derived from the error variances associated with the GPS position solution. This error region is superimposed on the road network to identify a road segment on which the vehicle is travelling. If an error region contains a number of segments, then the evaluation of candidate segments is carried out using heading, connectivity, and closeness criteria. For implementation purpose other parameters such as speed of the vehicle and distance to the downstream junction are used to improve the map matching process.

Advanced map matching algorithms

Both geometrical and topological map matching algorithms are used as the basis for developing other advanced map matching algorithms [41]. These advanced algorithms employ additional techniques to improve performance. These algorithms use concepts such as Kalman Filter or an Extended Kalman Filter, Dempster-Shafer's mathematical theory of evidence, flexible state-space model and a particle filter, an interacting multiple model, fuzzy logic model or the application of Bayesian inference [41, 46]. Some of these algorithms are discussed below.

The Kalman filter, one of the advanced map matching algorithm, is essentially a set of mathematical equations that implement a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance—when some presumed conditions are met. Kalman filter is the most effective method to filter signal with random noise [51]. Kalman filter operates in two distinctive stages: predictive (time update) stage and measurement update stage. It tries to estimate the state $x \in R^n$ of a discrete time controlled process governed by the transition and measurement equation defined as follows [51].

$$\begin{cases} X_k = \Phi X_{k-1} + W_{k-1} \\ W_{k-1} \sim N(0,Q) \end{cases} \quad (16)$$

$$\begin{cases} Z_k = HX_k + V_k \\ V_k \sim (0,R) \end{cases} \quad (17)$$

Where Φ is process state transition matrix, H is measurement design matrix, $Z \in R^m$ is measurement value at time t_k, Q and R are covariance matrices for the process error vector W_{k-1} and measurement error vector V_{k-1} respectively.

In the prediction stage, a new prediction of the error states (18) and error covariance states (19) are determined for the next step. The equation for the prediction stage are as follows.

$$\hat{X}_k^- = \Phi \hat{X}^+_{k-1} \quad (18)$$

Where $\hat{X}^-$ is the error state vector, ( ) indicates the a priori estimate while posteriori estimate is indicated with (+). And the predicted error covariance is defined as:.

$$P^- = \Phi P^+{}_{k-1} \Phi^T + Q \quad (19)$$

In the update stage, the Kalman Filter makes corrections to the predicted state estimate based on new information from the measurements. These corrections are appropriately weighed through Kalman gain (20) which determines if the prediction or the measurement should be trusted more. Then the Kalman gain is used to update the state estimate (21) and error covariance matrix (22) as the posteriori estimate for the next prediction stage.

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \quad (20)$$

After processing the measurement Z_k, posterior state mean estimation $\hat{X}^+$ is obtained by updating $\hat{X}^-$ with correct version of measurement residual.

$$\hat{X}_k^+ = \hat{X}_k^- + K_k (Z_k - H_k \hat{X}_k^-) \quad (21)$$

Then the covariance matrix P_k^+ associated with $\hat{X}^+$ can be updated from the priori estimate as:

$$P_k^+ = (I - K_k H_k) P_k^- \quad (22)$$

Provided that matrices Φ, Q, H, R are defined beforehand, the calculation of $P_k^-, K_k \, and \; P_k^+$ is independent of any measurement.

Particle filtering, based on a stochastic process, is another approach to the map matching problem. Particle filters are recursive implementations of Monte Carlo-based statistical signal processing [52]. Particle filtering provides natural way of incorporating the digital road map information in to the vehicle position estimation while the uncertainty of the road link the vehicle is moving occurred. The basic principle in this model is to use random samples (particles) representing posterior density of the vehicle position.

In dense urban areas, the vehicle trajectory taken from the positioning technology is often different from the actual vehicle route due to problems associated with the positioning technology used and the digital road map. For example, at a very high road density, many road patterns could be matched to the vehicle trajectory based on the data from positioning technology used but it will be difficult to precisely determine the road the vehicle is traveling. Hence map matching algorithm that suggests the link the vehicle more likely to be on one road and less likely to be on another is needed.

Fuzzy logic is a technique that deals with vague, imprecision and uncertain knowledge [53]. It is concerned with the use of fuzzy values that capture the meaning of words, human reasoning and decision making. Set of rules representing expert knowledge and experience is used to draw inference through approximate reasoning process. In map matching process, fuzzy logic can be used if the identification of the correct road link that the vehicle is moving becomes a qualitative decision making process with high degree of ambiguity. In this approach, the map matching algorithm is built with various expert knowledge and experience-based IF-THEN rules incorporating speed of vehicle, heading and historical trajectory of the vehicle, connectivity and orientation of the road link, the error contribution of the positioning technology and with the help of an optimal estimation technique, the physical location of the vehicle can be determined.

Error due to the positioning technology used affected the performance of map matching algorithms. Different methods are proposed to work with the sparseness and noises of GPS data. Recently, Hidden Markov Model (HMM) is shown to be effective in recovering the whole sequence of roads so long as the sequence of GPS measurements are used [54]. Hidden Markov Model is a statistical Markov Model in which the system being modeled is represented by a finite set of states, each of which is associated with a probability distribution [55]. Transitions among the states are governed by transition probabilities. Depending on the associated probability distribution, an outcome or observation can be generated at a particular state and it is only the outcome, not the state that is visible to an external observer. The general architecture of HMM is shown in Figure 10.

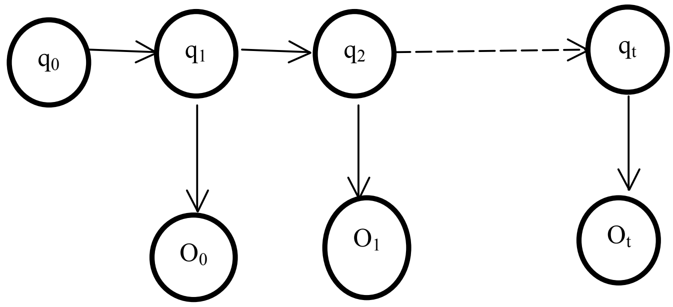


Figure 10. Hidden Markov Model Architecture

The architecture has two layers: $\{o_t\}$ represents the observable layer and ot corresponds to an observation value at time t. $\{q_t\}$ represents the hidden layer, and qt, at time t, comes from one state in a state space.
As map matching algorithm, the states (hidden layer) of the HMM are the individual road segments, and the state measurements (observable layer) are the noisy vehicle location measurements. The goal is to match each location measurement with the proper road segment. This state representation naturally fits the HMM, because transitions between road segments are governed by the connectivity of the road network.

IV. Road Traffic State Estimation

Road traffic state estimation is a fundamental work in Intelligent Transport System (ITS). It is applicable for dynamic vehicle navigation, intelligent transport management, traffic signal control, vehicle emission monitoring and so on. The two major components of ITS, Advanced Traveler Information System (ATIS) and Advanced Traffic Management System (ATMS) particularly need accurate current road traffic sate estimation and short term prediction of the future for smooth traffic flow [56].

Existing road traffic state estimation techniques can be grouped in to model based approach which are used for offline traffic state estimation and data driven approach for online state estimation [57]. Model based traffic state estimation approaches use the analytical traffic model Lighthill-Whitham-Richards (LWR) model [58] or simulation based models which are more suitable to model complex road traffic flows [59].

A. Model Based Road Traffic State Estimation

Traffic flow models can be categorized according to various criteria like level of detail, level of operationalization and level of representation of the processes. Depending on the level of details of the traffic system, traffic flow models can be microscopic, macroscopic or mesoscopic.

Microscopic traffic flow models

Microscopic traffic flow models describe both the space-time behavior of vehicles and drivers and also their interaction at a high level detail. This model simulates vehicle-driver units and analyzes properties like position and velocity of each individual vehicle. In this model road traffic is represented at each vehicle level and the interaction with each other and the road infrastructure. The interaction is captured as a set of rules that determines when a vehicle accelerates, decelerates, changes lane and also how and when the vehicle choose and change route to the destination.

Considering the vehicle's behavior, microscopic model can be decomposed into car-following model, lane-change model and route-choice model [60]. The car-following model describe the breaking and acceleration pattern resulted from the interaction of the driver and vehicle as well as other objects and the lane-changing model represents the driver decision to change lane based on preference and situation on the different lanes. The path drivers to take from origin to destination and the way they react to traffic and route information along the way is the route-choice model. The microscopic traffic flow model also enable to represent signs, traffic signals and also operation and location of traffic detectors. This model mostly is used to analyze traffic flow at each road network and number of vehicles travelling from origin to destination. Some of the microscopic traffic flow model simulators include INTEGRATION [61], HUTSIM [62], PARAMICS [63] and SUMO [64], VISSIM [65], MITSIMLab [66].

As a performance example, Tao et al. [67] used a microscopic simulation model to estimate road traffic sate using A-GPS traffic as probes. In the research, real-time location data is collected based on cellular network signaling and average link speed is calculated and aggregated to determine traffic state at each road link. The method is evaluated on a laboratory experiment using the microscopic simulation model SUMO (Simulation of Mobility). Liu et al. [68] also used the microscopic simulator VISSIM to evaluate Neural Network based traffic flow model which is developed to address the problem of urban arterial travel time prediction.

Macroscopic traffic models

Macroscopic traffic models describe traffic flow at high level of aggregation without distinguishing each of the vehicles. This model defines the relationship between traffic flow density, average velocity and road traffic flow or intensity [69]. The first macroscopic model was totally dependent on the fundamental diagram Lighthill-Whitham-Richards (LWR) model [58] referred as first order macroscopic model to determine traffic speed. To properly analyze traffic instability, delay responses and the anticipated behavior of drivers are important in macroscopic traffic flow model [70] which can explicitly be represented on speed dynamics under second order macroscopic model.

Compared to microscopic traffic flow models, macroscopic traffic models have minimum computational cost due to their few and directly measurable parameters. Moreover, due to high level of aggregate representation of traffic flow and road geometry, it is difficult to replicate and analyze traffic facilities. An example on its performance is the research work from Ziliaskopoulos et al. [71] where the researchers perform large scale dynamic traffic assignment applying cell transition model.

Mesoscopic traffic models

This model is a link between microscopic and macroscopic traffic model. Mesoscopic model fill the gap between the aggregate level approach of macroscopic and the individual interaction of vehicles and road infrastructure of microscopic ones. Mesoscopic traffic flow model describes the distance-density relation based on the distance link between two sequenced vehicles in microscopic model and traffic flow density on macroscopic model. These models are applicable when microscopic activities are desirable but difficult due to large road network and also during shortage resources for coding and debugging the network [72].

Hybrid traffic flow

Each of the above traffic flow models are with some limitations. For example, microscopic simulation models are known in detecting, analyzing and understanding large range of traffic problems but problems related to calibrating and cost and time of computation during simulation are the identified drawbacks of the model [72]. Although the calibration in macroscopic and mesoscopic models is easier than microscopic model, their application is limited to situations where vehicle interaction and drivers' behavior is not crucial to the results of simulation.

Different researchers have proposed and implemented a hybrid traffic flow model to overcome limitation of one traffic flow model by the advantages of another. Hystra , for example, is hybrid model combining macroscopic and microscopic traffic flow models [73]. According to the researchers, because Hystra is hybridized model it has minimized errors and also difficulty of calibration as it combines a flow and a vehicular representation of the classical Lighthill-Witham-Richards (LWR) model. MiMe [72] is also another micro-meso hybrid model. This model is a combination of the microscopic traffic flow model MITSIMLab and the mesoscopic model Mezzo. Based on the evaluation conducted using laboratory test as well as field data on the hybrid model MiMe, the authors obtained a promising result.

B. Data Driven -Based Road Traffic State Estimation

Online traffic state estimation methods are data driven approaches that use real-time measurements for real-time traffic state estimation. To represent real-time traffic state, travel time of vehicles on a certain road link is used. Travel time, which is defined as the time required to travel along a route between any two points within a traffic network [74], is a fundamental measure in transportation. Engineers and planners have used travel time and delay studies since 1920s to evaluate transportation facilities and plan improvements [75].

In recent times with the increasing interest in Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS), providing travelers with accurate and timely travel time information has gained paramount importance. Operators, for example, can use travel time information (current and/or predicted) to improve control on their networks as part of ATMS. Drivers also can choose their optimal route, either pre-trip or en-route, provided that traffic information from an ATIS is available together with the drivers' individual preferences. For transport companies the knowledge of travel time can help to improve their service quality. Moreover, they can choose their routes dynamically according to the current and predicted state of traffic and thus increase their efficiency and reliability.

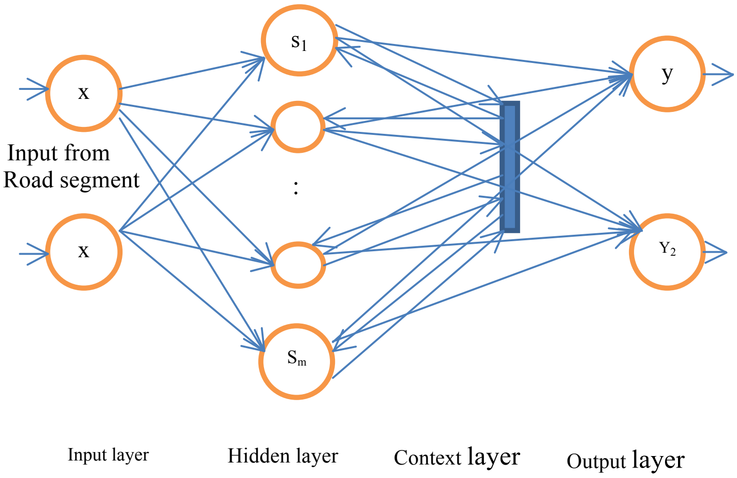
Because of this, a large number of research studies and literature reviews are concerned with the estimation, prediction and application of travel time in various areas of road traffic monitoring and management activities. One of the major issue in travel time estimation and prediction is the selection of appropriate methodological approach [76 Current practice involves two separate modelir approaches: parametric and non-parametric techniques [77

In the category of statistical parametric techniques, several forms of algorithms have been applied with greater weight to historical average algorithms and smoothing techniques. Autoregressive linear processes such as the auto-regressive integrated moving average (ARIMA) family of models also provided an alternative approach based on the stochastic nature of traffic [78]. Other statistical-based algorithms are based on the applications of linear and nonlinear regression, Filtering techniques, Bayesian and time series models [79]-[80] which are based on historical/real time data to forecast the travel time.

Some of the parametric algorithms also belong to multivariate time series model family. A good example for such kind of parametric technique is Kalman filter. The advantage of using Kalman filter algorithm in travel time estimation is that it enables the state variables to be updated continuously. The potential of the algorithm in travel time estimation is demonstrated in [81],[82]. Both Chien and Kuchipud [84] and Chen and chien [85] have used Kalman filtering for travel time estimation. The work of Tao et al.[67] also presented the use of Kalman filtering in urban traffic state estimation using A-GPS based vehicle location data. Moreover, the superiority of Kalman filtering over ARIMA is demonstrated in traffic state modeling during different period of the day [86].

The development of non-parametric techniques including non-parametric regression, neural network etc. has showed the potential to be an option against parametric methods. Some researchers demonstrate non-parametric techniques performing well due to the ability to capture nondeterministic and complex nonlinearity of travel time series [87]. Computational intelligence techniques like fuzzy logic, machine learning and evolutionary computation are also applied in travel time estimation.

Travel time prediction is a complex dynamic problem, it requires a data driven model capable of dealing with dynamic processes [88]. And one of the most popular computational intelligence techniques applied in travel time estimation is Artificial Neural Network (ANN). State space neural network (SSNN) model (Figure 14) is a First Order Context Memory [89], [90] consisting of four layers, an input layer) receives the input data and distributes section specific input vectors to the hidden layer. The latter also receives signals from the context layer, which stores the hidden layer states (that is, the hidden layers output) of the previous time instant. The output layer finally processes the hidden layer outputs and produces a scalar output, which is the mean travel time on the route of interest. SSNN can be used to model travel time along a signalized urban route where it can be depicted by connecting several urban segments (links and intersections) and can be treated as basic element of urban route.



C. Hybrid-Based Road traffic State Estimation

Road traffic state estimation is a complex activity which can't be done using a single forecasting method [91]. To use the data-driven approach, for example neural network, deployment of data collection infrastructure on road segments need high investment [88]. To train the neural network model based traffic state estimation methods like microscopic or macroscopic simulators can be used [92]. Hence, application of hybrid model based and data-driven road traffic state estimation reduces computational delay and also increases forecasting accuracy [91].

V.Classification Based on In-Vehicle mobile Localization Methods and Road Traffic State Estimation approaches Used.

A. Network-Based In-Vehicle Mobile Positioning

Network-based positioning technologies do not require major changes in the network and terminal but support to utilize the existing network infrastructure to provide location of the UE. These technologies have been an active research area since the issue of FCC in 1996. A research conducted by Sayed, et al. [93] used a simulator to compare the positioning accuracy of different Network-based positioning methods; AOA, TOA and TDOA in GSM network. From these location estimation methods, AOA and TOA are found to meet the FCC requirement, a location error below 100m for 67% of the calls made. The work of Al-Jazzar, et al. [94] presented the joint TOA/AOA positioning method and a simulation experiment resulted minimum Non-line-of-sight (NLOS) effect. To reduce the accuracy error in TOA/AOA hybrid positioning method, Kalman Filter is recommended and simulation based research conducted by Guangqian, et al. [95] showed that the theoretical position accuracy is further improved due to Kalman filtering applied in the hybrid Network-based positioning method.

The other network-based mobile positioning technology is U-TDOA. The major challenge in this positioning method in cellular network application is noise and multipath effect resulted due to Non-line of sight (NLOS) channel. The work of Mardeni, et al. [96] focused on the improvement of

UTDOA localization scheme using adaptive line enhancement (ALE) to pre-process signals heavily affected by noise and multipath before applying OTDOA. The authors used simulation test to validate as well as evaluate robustness of the proposed method.

Borkowski and Lempiäinen [97] and Jakub [98] conducted a research on Pilot correlation positioning method (PCM) for urban UMTS network. The researchers did their experiment on the method using UMTS network deployed in the urban environment. PCM is a finger print technique in UMTS which is based on Common Pilot Channel (CPICH) at the UE [99]. The CPICH power is measured for all Node Bs with the range and characterized throughout the area with the values modeled and stored in the database. The result of the experiment done on the position accuracy of PCM against Enhanced Cell-ID-RTT showed that the accuracy for 67% of the measurement was in the range of 70m-90m whereas for 90% of the measurement, the accuracy varies from 130m-195m.

A research conducted by Kunczier and Anegg [100] presented the use of Network-based positioning method for location based applications in urban areas. Because GPS and Cell-ID are not providing the expected accuracy of positioning, utilization of Bayesian Networks to improve localization accuracy of Cell-ID positioning method is proposed. To enhance the Cell-ID method, Network Measurement Report (NMR) based method which relies on received power level measurements is adapted. The achieved accuracy, based on measurements in the City of Vienna, is less than 20 meters in 67% of all estimates and about 50 meters in 90% of all estimates. Trevisani and Vitaletti [101] also showed how Cell-ID can be used for voice-based location services.

B. Handset-Based In-Vehicle Mobile Positioning

Handset-based mobile positioning methods are used when high position accuracy is needed. Different researches are conducted on the position accuracy evaluation and improvement of these position methods. One of the Handset-based mobile positioning methods is Observed Time difference Of Arrival (OTDOA). This positioning method suffers from near-far problem when the UE is close to Node B. Duffett-Smith and Macnaughtan [102] proposed Cumulative Virtual Blanking (CVB), technique used to take measurements of the downlink signal simultaneously at the handset and at Node Bs while position measurement is initiated [103], to overcome the hearability problem of the method and simulation based evaluation of OTDO supported with the new technique showed an accuracy of 20m in rural area.

In the same way, Ahonen and Eskelinen [104] conducted a research on the performance of standardized Observed Time Difference of Arrival (OTDOA) and a novel Database Correlation Method (DCM) for wide bandwidth systems. The evaluation of the proposed method through simulations in urban area confirmed that DCM provided a reasonable location error of 25 m for 67% of the calls. Ahonen and Laitinen [105] also conducted research to evaluate DCM against OTDOA and Cell-ID. Obtained results imply that DCM avoids most of the urban environment related problems and the simulation result showed a position accuracy of 25 m in 67% of the estimates, which is adequate for most location applications and it is also within the range required by emergency service.

Singh and Ismail [106] conducted a research to use the Handset-based positioning method OTDOA with the aim of generating 15% of location based traffic at peak hours in Malaysia. The simulation result showed a distance error of less than 12m but in average the error is more than 100m due to non-line of sight of Node Bs or additional time delay from multipath losses. The researchers recommended to use OTDOA in complement with Cell-ID if there are no proper alignments of 3 Node Bs. Handset-based mobile positioning using OTDOA-IPDL is detailed and implemented in [107] and the simulation result revealed that the location accuracy error in urban areas is 60m-115m for 67% of the cases.

Many Authors highlighted A-GPS with high accuracy at reasonable cost and also fits the FCC positioning requirements [108]-[109]. And most researchers used A-GPS to improve limitations of other mobile positioning methods as it is discussed in hybrid positioning method.

C. Hybrid In-Vehicle Mobile Positioning

Different Authors conducted a research on hybrid mobile positioning methods aiming to complement downside of one method with the other method to provide better performance measure. Adusei et al. [27] discussed four possible hybrid positioning methods without conducting experiment to evaluate their performance. The methods include:

Cellular-Cellular Combination: Hybrid of AOA and TOA reduces signaling load because only one BS is required. Whereas hybrid of E-OTD and Cell-ID-RTT greatly improves availability.

GPS-Cellular Combination: Hybrid of GPS and EOTD or GPS and Cell-ID-RTT gives good availability and good outdoor accuracy. Besides, the same cellular network elements can be used to support both technologies.

GPS-Inertial Sensors: Enhanced GPS (EGPS) is an example for this hybrid positioning method. And the accuracy of this combination is within 1m and 30m in urban and suburban areas respectively.

GPS-Cellular- Inertial Sensors: A very high complexity, but superior availability and good accuracy could be hybrid of A-GPS, EOTD and low-cost low power inertia navigation system (INS). The author didn't evaluate any of the above hybrid positioning methods.

Hybrid mobile positioning methods combining Network-based with Handset-based and also fusion of two Handset-based positioning methods for vehicle positioning are discussed in the work of Tao et al. [12], [19]. Under the combination of two Handset-based positioning methods, hybrid of A-GPS and OTDOA is described. The experiment result in [19] using a simulator showed that the hybrid positioning method has better accuracy compared with the individual positioning methods. On the other hand, hybrid of Cell-ID and A-GPS, U-TDOA and A-GPS are discussed within the combination of Network-based and Handset-based positioning methods. Hybrid of Cell-ID and A-GPS is found to be the simplest and reliable UE positioning method and recommended to offer adequate positioning for vehicle location. Hybrid of U-TDOA and A-GPS is preferred for UE positioning as U-TDOA has better accuracy compared to Cell-ID and also doesn't require handset modification. In this hybrid positioning method, A-GPS provides positioning function when it is available otherwise the Network-based U-TDOA would be used. The work of Abo-Zahhad, et al [110] also described U-TDOA and A-GPS hybrid positioning method with respect to accuracy, latency, call state environment and system loading parameters and concluded that for mobile position based applications, the hybrid method provide high accuracy without time delay and preferred for outdoor applications with light system loading but U-TDOA is selected for indoor applications and with heavy system loading.

The work of Drakoulis, et al [111] presented Hybrid positioning method based on the well-established positioning techniques GPS and the Network-based positioning method TDOA in GSM network. The author evaluated the performance and the compliance of the method with respect to related standards. Son et al.[112] also introduced an integrated method for GPS pseudo ranges and wireless network TDOA measurements to solve the radiolocation problem when the number of visible satellites is not sufficient. They adopted the least squares method for evaluating user position and the Kalman filter (KF) for Non Line Of Sight (NLOS) error measurement. Broumandan et al.[113] analyzed the positioning performance using a TDOA/AOA hybrid system in CDMA network. Chen and Feng [114] presented a hybrid location scheme, which combines both the satellite-based (GPS) and the Network-based positioning methods. In the hybrid positioning method GPS, TOA, TDOA and AOA positioning techniques are combined as UE-assisted and UE-based positioning methods. The authors used least square method to determine position of the UE, Kalman filtering to reduce error and track UE trajectory and Bayesian Inference model to merge TOA and TDOA/AOA estimations. Based on a simulation result, the hybrid positioning method provided consistent location estimation accuracy under different environments. Chen and Abedi [115] also experimented using a simulator on hybrid positioning methods based on Received Signal Strength (RSS), TOA, TDOA and AOA in W-CDMA network. The simulation result indicated, the hybrid estimation scheme combining RSS, TOA, TDOA and AOA data achieves higher positioning precision than that of the RSS-only, the TOA-only, and the TDOA-only or AOA-only methods.

To improve latency and enhance availability of A-GPS positioning method, Borkowski, et al. [116] have proposed to combine Network-based positioning method and Handset-based positioning methods with A-GPS. The proposed assistance methods include PCM, which is entirely Network-based method in UMTS [97], and signal strength measurement together with Cell-ID in GSM network. The simulation experiment conducted on the hybrid positioning method PCM and A-GPS in urban UMTS network provided accuracy below 70m for 67% of the location request and 130m-190m accuracy for 90% of the request. Whereas Hybrid Handset-based positioning methods based on A-GPS and Cell-ID + Signal Strength operated in rural GSM network provided accuracy below 300m for 90 % of the location request.

D. Mobility Classification

Vehicle location data collection using mobile phones as traffic probes consists of different mobile phone carriers. To discriminate mobile phones in moving vehicles from other mobile phones, different researchers used different approaches. For example, Choi and Tekinay [39] applied location registration mobile carriers are classified into two broad groups: predictable and unpredictable mobile. Using location update signal cost, predictability (when update signal cost is low) and unpredictability (update signal cost is high) is determined. However, practical implementation of the classification approach is not considered.

Puntumapon and Pattara-Atikom [40] proposed to use Naïve Bayes model to classify sky train and pedestrian mobility from mobile device information based on the number of unique Cell-ID and their average dwell time. Cell dwell time is the duration between two registration operations of a mobile device on the nearest base station while in motion.

Naive Bayes is a model for clustering and classification based on Bayes Theorem. This model estimates the per-class probability by assuming that the attributes are conditionally independent. Let C denote class variables used for classification, E_i denote conditional attribute i used for classification and $P(C|E_1, ...,E_n)$ denote conditional probability of class C given that the evidence $E_1,...,E_n$ have happened. The probability model for a Naive Bayes classifier can be defined as follows:

$$p(C/E_1,...,E_n) = \frac{p(C)xp(E_1,...E_n/C)}{p(E_1,...,E_n)} \quad (23)$$

Using joint probability model, Chain rule and repeated conditional probability equation (2.23) could be derived as:

$$p(C/E_1,...,E_n) = \frac{p(C)xp(E_1/C)xp(E_2/C)x...xp(E_n/C)}{p(E_1,...,E_n)} \quad (24)$$

The authors concluded that Naïve Bayes model based on the number of unique Cell-ID and the average Cell dwell time of unique Cell ID has a performance of sky train and pedestrian mobile device classification accuracy up to 93.1%. And they recommended the model to be applied for large data sets and vehicle mobility classification.

E. Map Matching

Map matching algorithms integrate estimated locations from any kind of positioning sensors with spatial network data on a digital map to identify the correct link on which a vehicle is travelling and to determine the location of a vehicle on that link [117]. Among the traditional map matching algorithms, the most common method is the geometric map matching approach which uses the geometric information of the road [45]. White et al.[47], Srinivasan et al.[118] and Bouju et al. [119] conducted comparison analysis on the geometric map matching algorithms, point-to-point ,point-to-curve and curve-to-curve approaches and concluded that accuracy problem can't be solved only using geometric map matching.

Point-to-curve geometric map matching is also used to reconcile vehicle location determined using TOA/AOA mobile positioning technology [120] and A-GPS [67] on a digital road map. And in the conclusion it is discussed that using Non-Line-of-Sight (NLOS) Least Square (LS) method together with map matching algorithm increases the position accuracy.

The work of Gundlegard and Karlsson [37] discussed the importance of map matching when using location data from cellular network. The authors based on the sampling measurement rate that results from location positioning technologies used recommended to apply Point-to-Curve geometric map matching algorithm for Mobile-based/Active monitoring and Curve-to-Curve geometrical map matching algorithm if Network-based monitoring /Passive monitoring is used to gather location of vehicles as the sampling rate of the former is low and for the latter is high.

Another map matching method is topological approach which uses link's geometry, connectivity and contiguity in the matching process. Different researchers have worked on the improvement and evaluation of topological map matching algorithms. GreenFeld et al. [44] for example proposed a weighted topological map matching algorithm which depends on topological analysis of road network using coordinate information for the position of the vehicle. The weighted scheme of the algorithm is based on the perpendicular distance of the position fix from the link, degree of parallelism between the line and the link and the intersecting angle. The total weight score for a particular link is given by:

$$W_t = W_d + W_p + W_i \quad (25)$$

The authors then determine the vehicle location on the link using orthogonal projection. This method is very sensitive to outliers as these can lead to the determined vehicle heading to be inaccurate. The work of Quddus et al. [121] is another which discussed topological map matching algorithm enhancement based on similarity criteria between the digital road network and navigation data. Vehicle speed, position of the vehicle with respect to the target link and heading information from the positioning technologies GPS/DR are used to improve the performance of the algorithm. Based on a field test evaluation of the algorithm, the authors concluded that the algorithm is very efficient at junctions and intersections. Moreover, the estimation of the vehicle location on the appropriate road link is found to be robust as errors due to bearing and positioning technologies were controlled. Wang and Yang [122] also proposed topological map matching algorithm to map moving vehicle on to vehicle road link using GPS vehicle location data. The algorithm is tested on a simulation in four road intersections and recommended that it provides high accuracy and solves spatial problems in complex vehicle road networks and also fulfills map matching in real time. The work of Blazquez [123] also discussed how spatial ambiguity can be resolved using decision-rule topological map-matching algorithm.

The work of Velaga et al [50] described an enhanced weight-based topological map-matching algorithm for Intelligent Transport System (ITS). The weight values are determined from real world field data. The weights for turn-restrictions at junctions and connectivity are used and checks are done to reduce mismatches. The authors tested the algorithm using a real data under different operational environment and concluded that the new features added have improved performance of topological map matching algorithm. But, according to the authors, the optimal algorithmic weights for different factors such as heading, proximity, connectivity, and turn-restriction still need to be estimated with a range of real-world field data from different road environments.

Meng et al.[49] also used topological analysis based on the correlation of the trajectory of the vehicle and road features (road turn, road curvature and road connection) to develop simple map matching algorithm. The algorithm is developed using data from GPS/DR and digital road map including information about road junctions. The authors conducted different tests to identify road segments which don't fulfill statistically determined threshold. The authors concluded that the algorithm can enable to correctly identify vehicle in the correct link even at real-time but the algorithm is sensitive to outliers and also doesn't work at junctions where the bearing of the connecting road is not similar.

Ochieng et al.[43] proposed enhanced probabilistic map matching method that require definition of the error region of the ellipse when the vehicle travels in a junction. The algorithm is applied to determine the location of the vehicle and also in the identification of the road link that the vehicle is moving. The authors tested the algorithm off-line in a complex urban road with different traffic situation and provided a 100% correct matching and concluded that the algorithm has improved uncertainty of the vehicle position in addition to resolving problem of inaccurate road map data with the inaccurate vehicle location data.

Many researchers have also applied the Kalman filter theory to their map-matching models to solve spatial mismatch. For example, Kim et al. [124] proposed a map-matching algorithm consisting of model of biased error and Kalman filter. The developed navigation system uses an integrated GPS, DR positioning technology. The authors first used Point-to-Curve matching algorithm to identify the correct road link of the vehicle. Then to get the initial location of the vehicle, orthogonal projection of the estimated positions on to the road link is done. Though orthogonal projection reduces cross-track error, along- track error is a big issue in the map matching process. So, the researchers applied Extended Kalman Filtering (EKF) to re-estimate the vehicle location with minimum along-track error. The authors, based on results of the real world experiment, concluded that the algorithm was effective in minimizing along-track error and need to be improved using heading, speed and topological feature of the road network as parameters in selecting correct road link. Xu et al.[125] also proposed an improved Kalman filter algorithm with effective GPS error correction approach. The Kalman filter in the proposed map matching algorithm filters the white noise error and corrects the biased error in both the cross-track and the along-track directions. The algorithm is tested in real world situation and observed that the algorithm provided an improved accuracy and reliability. Similarly, an improved map-matching algorithm that employs Kalman filtering to filter unreasonable GPS data and the Dempster-Shafer (D-S) theory to correctly snap GPS vehicle coordinates to the digital road map is proposed in [126]. The D-S theory is used for the representation of ignorance and combination of evidence and it operates with a smaller set of uncertainties. Based on a real world experiment conducted, the authors concluded that the improved algorithm is effective and applicable though verifying the accurate performance of the algorithm is needed in further research.

Some new methods like particle filter, fuzzy logic (Fu and Wang[127], Zhang and Gao[128], Jagadeesh et al. [129], Yang et al.[130]) and Hidden Markov model were also proposed recently for map matching. Different literatures discussed the performance of particle filter to match the sensor based vehicle positions on to digital road map. Gustafsson et al. [52] for example developed a framework for navigation, tracking and positioning problems using particle filtering. The general algorithm is evaluated in matching the aircraft's elevation on a digital elevation map and the vehicles horizontal driven path on to a digital street map. A real-time map matching implementation is done and the test result showed good accuracy. The authors also recommended particle filter to be used for cellular network based positioning measurements in tracking vehicles. But determining nonlinear relations and non-Gaussian models that provide the most information about the position of the vehicle is still a challenge. Hence the authors recommended for further research to seek a reliable way to detect divergence and restart the filter. The work of Toledo-Moreo et al. [131] is another one which discussed multiple-hypothesis particle-filter based algorithm to solve the map-matching problem with integrity provision at the lane level. The proposed model integrates measurements from a GPS receiver, an odometer, and a gyroscope along with road information in digital maps. Experiments were done on two different cities with two prototypes based on different sensors. A set of six experiments were conducted with real data for a period of 30 minutes proving positioning, map matching and integrity provision for lane-level applications and to achieve full integrity, the authors mention that outlier removal, multipath effect mitigation, and additional method validation need to be addressed. Davidson et al. [132] also developed and demonstrated numerical probabilistic approach for map matching problem based on particle filtering to improve positioning accuracy and vehicle navigation activity.

Particle filtering is preferable for nonlinear and non-Gaussian systems than Kalman filtering [133]. But particle filtering diverges and causes degeneration with high measurement precision. Crisan and Doucet [134] presented a survey on the convergence results of particle filtering methods and concluded that most convergence results rely on strong assumptions which make the methods difficult to be applied in real world problem and recommended future research on the performance improvement of particle filtering. In relation to this Xue et al. [135] discussed filtering improvement method in reducing navigation error and increasing accuracy of performance. The authors used GPS/DR positioning systems and carry out a simulation for comparative analysis between the standard particle filtering and the improved algorithm named robust auxiliary particle filtering. Because one of the robust estimation method- maximum likelihood estimate with an equivalent weight is used in sampling and re-sampling of particles (vehicle positions), the latest measured values were considered and the particle degradation slows down. And this has improved the precision of the map matching process with real time performance.

Fuzzy logic based map matching algorithms are developed by a number of researchers. The research conducted on adaptive fuzzy-based C-measure algorithm [136] is for example capable to identify the road way on which the vehicle is traveling by comparing C-measures associated with each candidate road links. The C-measures are membership functions representing the certainty of vehicle existence on a road link. Orthogonal projection is applied to determine the position of the vehicle based on the identified route. But for proper use of the algorithm, there are some requirements like distance between vehicle position and its projected position need to be small and also the shape of the road way needs to be similar to the vehicle trajectory. The authors conducted real road experiment based on GPS data and recommended real time applicability of the algorithm. Syed and Cannon [137] also discussed fuzzy logic based map matching algorithm using GPS/DR data. The algorithm identified the correct link of the vehicle and also the position of the vehicle on the identified link. The result based on a field experiment conducted for about 15 minutes considering low signal availability with variable speed of the vehicle showed that this algorithm is far better than geometric based map matching algorithms. But the process of determining the correct link of the vehicle is time taking and also error prone due to positioning technology and road map were not considered.

Quddus et al. [42] described high accuracy map matching algorithm based on fuzzy logic theory. The authors discussed limitations of the other map matching algorithms including previous studies on fuzzy logic and proposed an improved fuzzy logic approach that could solve the limitations identified. The input variables considered include vehicle speed, road link connectivity, quality of vehicle positioning technology, relative position of the identified vehicle position with respect to the candidate road link and three set of knowledge-based fuzzy rules. The authors tested the algorithm in different road networks in different environment and found that the performance in correct link identification is better than other map matching algorithms and also the along-track error and cross-road error of this algorithm is minimized. Because the position accuracy of the algorithm in urban areas was not evaluated in the experiment, the authors recommended it for future research.

Another map matching algorithm based on integrated fuzzy logic theory and look-ahead technique is proposed in [138]. The authors used vehicle position data collected from cellular network based on Time Of Arrival (TOA) positioning technology (i.e. position of phone in moving vehicle) and solved a map matching problem for road traffic information. The algorithm compares the similarity degree of phone in moving vehicle running road and the candidate roads to determine the road that the vehicle is travelling. Subsequently, fuzzy preference relations considering the similarity coefficients, projection distance, directional angle and run distance are adopted to perform a multi-criteria decision and a look-ahead technique is employed to improve the matching accuracy. The validity of the approach is tested using a simulator and the authors proposed to include other cellular network positioning techniques to improve the matching accuracy.

Because of the error on the positioning technology, the performance of the above map matching algorithms is affected. The map matching algorithm proposed to work with sparseness and noises positioning data is Hidden Markov Model [54]. Reymond et al. [139] also proposed a Hidden Markov Model based map matching capable to cope with noise and sparse of GPS raw data. The algorithm used points sampled on the road map data as hidden states in the HMM framework and this enabled the state transitional probability to fit with Viterbi algorithm (i.e. an algorithm for finding the most likely sequence of hidden states). The algorithm is tested in a real world data using different sampling rate of points. The authors concluded that 46% of road data is needed for sufficient map matching using this algorithm when there are low rate GPS trajectories and proposed to identify best sampling rate of the road network map for map matching in the future. Similarly, Goh et al.[140] proposed to use HHM for an online map matching and tested the algorithm using real world data. The algorithm decides the sequence of roads incrementally based on the new position measurements obtained. But the method has a complexity problem when modeling the map matching in the HMM framework.

F. Road Traffic State Estimation

Travel time estimation in urban road networks is very important for many intelligent transport system applications like ATIS and ATMS. These systems basically aim to provide information to drivers or control centers on current traffic flow condition which can help to handle unexpected incidents taking place on the road network. Road traffic state estimation techniques are model based, data driven or hybrid approaches. For real-time traffic state estimation data driven approaches are preferable [57]. Current practices on travel time estimation on urban roads applied parametric and non-parametric methods. Table 11 provides list of the current literatures on the implementation of short travel time prediction methods in urban networks.

As it can be seen from Table11, both parametric and non-parametric methods are applied. But most studies used non-parametric methods in urban networks because it is more efficient as it cope with the fluctuating nature of traffic parameters like traffic flow, speed etc. Particularly, Artificial Neural Networks have been applied extensively in short term traffic forecasting field and acknowledged to be a promising approach because of its superiority in modeling complex nonlinear relationships [156], [157] and [158].

Table 11. Literature review for travel time estimation methods in urban road networks.

	Data for travel time estimation			Methodological approach		Type of data used	
Authors	flow	speed	other	parametric	Non-para metric	Real-time	simulation
Kamarianakis and prastacos [141]		x	x	x		x	
Stathopoulos and Karlaftis[86]	x			x		x	
Vlahogianni et al.[77]	x				x Non-parametric regression		
Clark [142]	x	x			x Non-parametric regression		
Yang [143]			x	x		x	
Vasudeva and Wunderlich [144]			x		x Neural Network	x	
Batool and Khan [145]	x				x Neural Network	x	
Guin [146]	x				x Non-parametric regression	x	
Liu et al.[147]	x			x		x	x

Liu et al.[68]	x				x Neural Network	x	x
Fabritiis et al.[148]		x			x Neural Network	x	
Zhu et al.[149]			x	x		x	
Liu et al.[90]	x				x Neural Network	x	
Dong et al.[150]	x			x		x	
Wei et al. [151]	x				x Neural Network	x	
Chen et al. [152]		x			x Neural Network	x	
van Hinsbergen et al.[153]			x		x Neural Network	x	
Wang et al.[154]		x			x Non-parametric regression	x	
Yang et al. [155]		x			x Neural Network	x	

Artificial Neural Networks have other advantages over other methods that make researchers choose them as road traffic modeling tool [77]. Strong adaptability of Artificial Neural Networks enabled them to learn from past data. Because they are data driven models, their transferability is strong and also need little experience when applied to different road traffic networks. Moreover, Artificial Neural Networks are very flexible in producing accurate multiple step-ahead forecast with less effort. Vlahogianni et al. [77] presented summary of various characteristics of neural networks together with other parametric and non-parametric methods as shown in Table 12.

Artificial Neural Networks have also some limitations like their “black box” nature, there are so many types of Artificial Neural Networks and as existing researches proved, appropriate network topologies and configurations can greatly affect performance of Artificial Neural Networks models [159]. But still there is no standardized criterion to identify the most appropriate Artificial Neural Network model. Current researches follow a trial-and-error method to find the optimal scheme.

Table 12. Characteristics of parametric and non-parametric modeling techniques for travel time estimation [77].

Characteristic	Parametric methods			Non-parametric methods	
	smoothing	ARIMA	Kalman Filter	Non-parametric regression	Neural Network
Quality of data	Short series	extensive	extensive	extensive	extensive
Accuracy	low	low	medium	high	high
Nature of prediction	static	recursive	static	dynamic	dynamic
Advantage	Short series needed	Theoretical back ground needed	Multivariate nature	Simple model structure	Wide mapping capability
Disadvantage	Low accuracy	Low accuracy Slow data processing	Gaussian hypothesis	Intensive data	Intensive data Complex internal structure

To overcome limitation of one data driven forecasting model by advantage of another, different researchers have been using hybrid models (combining parametric and non-parametric methods). For example, Yin et al. [160] developed fuzzy-neural model (FNM) to predict the traffic flows in an urban street network. Alescsandru and Ishak [161] also presented a model-based and memory-based hybrid system to improve performance of freeway speed forecasting systems. Zheng et al.[162] developed a

Combined Neural Network Model (CNNM) for short-term freeway traffic flow prediction and Van Lint et al. [163] applied a Kalman filter neural network to forecast short-term travel time on freeways.
Because data driven approaches need intensive data, hybrid (combination of model based and data driven approach) urban road traffic state estimation method is applied in recent literatures. The research work of Anderson and Bell [92], for example, used the model based microscopic traffic flow VISSIM with Neural Network for traffic state estimation techniques and a queuing model for travel-time prediction in urban road networks. The work of Tao et al. [67] also presented the use of Kalman filtering integrated with a microscopic simulation model SUMO in urban traffic state estimation using A-GPS based vehicle location data.

VI. Conclusion

Mobile positioning Technology

First and second generation cellular networks are not dedicated to location services (LCS)[12]. On the other hand, third and fourth generation cellular networks have protocol requirements for LCS. Third generation cellular network (UMTS) is with better inherent position accuracy when compared with GSM and CDMA [21] due to the increase signal bandwidth and shorter bit period, as these attributes improve the ability to distinguish the line-of-sight signal among multipath returns during reception. Moreover, third generation cellular network has been deployed pervasively worldwide and UMTS Forum confirmed that subscription to 3G/UMTS reached 500 million in January 2010 [164]. In Africa, the mobile subscription growth rate is easily outstripping the mature mobile markets elsewhere in the world. GSM (2G) mobile subscriptions now account for 62.7 % of mobile subscriptions in Africa, while 3G represents
11% of the overall market and it is expected to grow to 1.12 billion subscribers by 2017 contributing 13.9 % to take the global cellular market to 8.11 billion [165] . In relation to this, state-owned telecom monopoly (Ethio-telecom) announced to upgrade the current 3G network telecommunications infrastructure to 3G LTE (long-term evolution) networks [166]. While launching the current 3G cellular network in May 2012, Ethio-telecom announced that it was ready to deploy the service for 300,000 subscribers in Addis Ababa [167]. Hence, proposed solution and further discussions focused on UMTS (3G) network as it is standardized well established and widely deployed.

In relation to this, the four standard LCSs in UMTS are presented and evaluated. None of them is perfectly suitable for vehicle location. The decision which class of mobile positioning method to use primarily depends on the characteristics of the location based service.
Network-based mobile positioning methods are preferable to system operators for two basic reasons. The first one is network operators' concern in relation to smooth migration of the network to support location functionality and the other is subscribers' concern where they refuse to exchange or to modify their devices solely in order to use the new network features that go along with the upgrade. And cellular network operators give higher emphasis for the implementation of at least one Network-based mobile positioning method in supporting location services.

Network-based mobile positioning methods in general have some limitations. Cellular networks using these methods may experience reduced capacity. The accuracy of network-based positioning depends on network-based factors including cell size and density, and in the case of TDOA based technologies, the location of the several base stations within hearing of the mobile unit. Besides, if the cellular network is not a 3G network, network-based mobile positioning methods may involve significant infrastructure change and investment.

Handset-based mobile positioning methods are preferable to secure location data and because the method doesn't use resources and facilities of the network, using these position methods don't affect the network capacity. More importantly, this method can help to improve location accuracy by taking more measurements as the handset is not limited by the network. In relation to this, Mohan, et al [168] proposed Handset-based mobile positioning method is a suitable traffic monitoring approach for low and middle income countries because of the following reasons. The road and traffic condition on these countries unlike the developed once is more varied due to various socio-economic reasons. For example, road quality is variable, bouncy roads are common even at the center of cities, the flow of traffic could be chaotic with no adherence to standards and vehicle types are also very variable. So, monitoring such varied traffic condition is difficult unless very rich sensing (location measurement) method like handset-based is used. Moreover, this approach avoids the need for expensive and specialized traffic monitoring infrastructure and can also take advantage of the booming growth of mobile telephones in the countries.

Handset-based mobile positioning methods have also a drawback of requiring special, more expensive and higher power consuming mobile phones. These methods have no potential to locate existing mobiles and may require synchronization.

Inspired by the above discussion of the standard location methods, it is straightforward to expect that hybrid mobile positioning methods can complement the limitations of one method with the advantages of another. In different literatures, attempts have been made to pursue hybrid mobile location and tracking [111, 112, 169, 170]. This is because hybrid mobile positioning methods like Handset-based positioning methods can help to track many mobiles to improve accuracy, take advantage of transmissions originating from other networks, not to be affected by frequency hopping and because the methods are simpler to implement with no modification on the network, different researchers tried to demonstrate experimentally [171]. However, they still leave the doors open for further investigations. Most of these researches are based on 2G cellular network location techniques and only a few of them use the 3G standard location methods. In the hybrid positioning method, most aim to complement GPS performance not the more recently evolved A-GPS and they hardly target vehicle location applications which will make difference in performance requirements.

Future works

Cell-ID based positioning is the simplest and most reliable Network-based UE positioning method. But its accuracy can't meet vehicle location requirement service. To improve accuracy of Cell-ID positioning method, different standards are implemented. In UMTS, Cell-ID+RTT can be an example. This enhanced Network-based positioning method is claimed to estimate the distance between UE and BS with accuracy of 36m [15]. Moreover, the great widespread of indoor and outdoor cellular network can enable better position location accuracy in the future.

In contrast, A-GPS UE positioning method provides excellent location accuracy, especially in open-space. Because it is network assisted, latency and positioning problem in dense urban environment is solved. Moreover, A-GPS phones gained significant market share in the mobile handset and personal computer markets, and this trend is expected to continue in the near future. According to Canalys [172], GPS-enabled Smartphone shipments were 43.7% of all handset shipments in 2012, and its share in the handset market is expected to grow to 65.1% , which is 2.6 billion units, in 2016 worldwide. Particularly in Africa and Middles East, GPS-enabled Smartphone sales volume rate rises to 56% in 2013 where the rate of growth in Africa is almost two times higher than the global average growth rate [173]. In Ethiopia also, Hong Kong-based mobile manufacturer Tecno Mobile released its first assembled Amharic language based Smartphone in 2012 [174].

The best positioning accuracy for A-GPS is achieved in rural environment but in urban areas it is affected by shadow of high buildings. Hence supplementing A-GPS with inexpensive positioning method is preferable. In relation to this, the Integration of improved Cell-ID and A-GPS can provide adequate positioning estimation for vehicle location [12, 30].

Another option for Network-based, Handset-based integration UE positioning is to use U-TDOA instead of Cell-ID. U-TDOA has better accuracy compared to Cell-ID as well as OTDOA and don't require the handset modification. Hence, the combination of U-TDOA and A-GPS for UE positioning for vehicle location provides better accuracy. The Integration can be done in two ways. Both U_TDOA and A-GPS can simultaneously be used in vehicle location activity or by default A-GPS can be used and when not available the robust positioning technique U-TDOA would take over.

Based on what we have discussed above, the following need to be investigated to implement vehicle location using the cellular network infrastructure. The first one is to develop / identify suitable emulator to simulate Cell-ID or U-TDOA positioning methods. The second one is to use fusion algorithm to combine position measurement obtained from either Cell-ID or U-TDOA and A-GPS based location data. The third is to perform a real-time road traffic state estimation based on the location measurements.

Cell Phone Mobility Classification

According to the literature, several studies explored methods to use the cellular network to estimate road traffic flow and detect congestions. Most of these studies didn't discuss the technique applied to filter out the irrelevant data before feeding to estimation and prediction algorithms. But the data collected using the cellular network consists of various types of mobile carriers, carried by pedestrians, stationary phones, etc. However, our interest is to track terminals that are found in-vehicles travelling on the road network. Therefore it requires pre-processing to identify the irrelevant traffic data from relevant data set.

Different terminal classification approaches like Naïve Bayes model, location registration scheme, Speed, direction, location update interval, erraticity, fusion of speed, direction and location of terminal as it is discussed in section 5B, are proposed on the literature but none of them was experimentally tested and recommended to be used in vehicle mobility classification.

Naïve Bayes model is a simple probabilistic classifier based on Bayes' theorem with strong (naive) independence assumptions. Naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. In spite of their naive design and apparently over-simplified assumptions, naive Bayes classifiers have worked quite well in many complex real-world situations. The work of Zhang [175] discussed the theoretical reasons for the efficient and effectiveness of naive Bayes classifier. One of the reasons for the competitive performance of naïve Bayes model in classification is that it allows the class conditional densities to be calculated separately for each attributes and reduces a multi-dimensional task to a number of one-dimensional tasks. A good example in relation to this the application of naïve Bayes model in classifying sky train and pedestrian mobility[40] where the accuracy of the classifier is experimentally evaluated and also recommended to be applied for vehicle mobility classification.

Hence, in this research to classify in-vehicle terminals traveling on the road network from others terminals carried by pedestrians, held by motorcycles and bicycles, stationary terminals, etc. naïve Bayes classifier will be used and based on experimentation its accuracy will evaluated.

Map Matching Algorithms

Map matching is the process of determining the correct road link of a moving vehicle and locating its position on the link. Different algorithms are developed and published in the literature. These algorithms used position data and digital road map in the course of matching. Positioning technologies, for example the most used are GPS/DR, are indispensible to vehicle location activities. These technologies as well as the digital road map used during matching can affect the performance and accuracy of the map matching algorithms.

The simplest map matching algorithm is the geometric Point-to-Point and Point-to-Curve map matching algorithm. These algorithms don't use historical information about the vehicle and may result in mismatch. In Point-to-Curve matching, matched position can oscillate between two closely situated parallel roads especially in dense urban street networks.

Some of the drawbacks of the Point-to-Curve method can be solved by another geometric method known as Curve-to-Curve map matching algorithm. The Curve-to-Curve method matches the piecewise linear curve formed by the sequence of estimated positions to a piecewise linear curve corresponding to a path in the network based on their closeness or similarity. The drawback of this algorithm is that the vehicle heading is not considered.

Map matching algorithms that make use of the Point-to-Point, Point-to-Curve or Curve-to-Curve mapping can be improved by incorporating topological information such that only those road segments that are directly connected to the current road of travel are considered.

Probabilistic map matching algorithm is another approach that makes use of statistical error models of the positioning sensor to define a confidence region within which the true vehicle position may lie. In this algorithm only roads that lie within this region are considered for map matching. Although these algorithms can recover from wrong matches quickly, they require more computation time. In dense urban road networks, it is difficult to precisely identify the road on which the vehicle is travelling. Hence advanced map matching algorithms using concepts like Kalman filtering, particle filtering, fuzzy logic etc. are proposed. The map matching algorithm that enables to determine whether a vehicle is more likely to be on some roads and less likely to be on other roads is Fuzzy logic based map matching algorithm. This algorithm can deal with ambiguous situations and support for decision making based on degree of ambiguity.

Performance of Geometric, Topological, Probabilistic and fuzzy logic map matching algorithms are evaluated with respect to correct link identification, horizontal accuracy and along-track and cross-track errors and Fuzzy logic map matching algorithm gives best result from all map matching algorithms evaluated on the same test road network based on GPS data[117]. Performance comparison between fuzzy logic and Hidden Markov model in terms of accuracy, computational time and implementation complexity is done using a GPS data on the same test road network for pedestrian navigation[41] and Hidden Markov Model based map matching performs better in accuracy and computational time than fuzzy logic based although its implementation is complex.

From the map matching algorithms reviewed above; we can say all used GPS or integration of GPS and DR positioning technologies to evaluate performance of the algorithms. As it is proposed in section 8, cellular network signaling particularly hybrid-Positioning is going to be used in this research work. Since error due to positioning technology affects the performance of map matching algorithms, we proposed to perform an experiment on Hidden Markov Model and Fuzzy logic theory based map matching algorithm using Hybrid-based vehicle position data and implement the better performing algorithm.

Road Traffic Estimation

Traffic state estimation has become more important to our daily life particularly with the rise of urban development. It is essential for intelligent transportation system, dynamic vehicle navigation, traffic signal control, transit scheduling systems, vehicle emission monitoring, emergency dispatching services etc.

Advanced traveler information system (ATIS) is one of the most principal subsystems of intelligent transportation systems (ITS) that offer users integrated traveler information. One form of user's information presented is the real time traffic state, which is also used by network operators as an indicator of quality of service. This raises the interest of estimating road traffic sate with an acceptable degree of accuracy and travel times and average velocities have always been of great interest to researchers in order to estimate traffic sate of a road network. Model based and data driven approaches are the two methods researchers applied in road traffic state estimation. Depending on the detail level of traffic state estimation system, models like microscopic, macroscopic, mesoscopic or a hybrid of them are used in different literatures as a tool to properly estimate urban traffic flow. These model based traffic flow predictors enable to predict traffic condition for certain number of time period ahead and also deduce average travel time from these predicted traffic flow conditions.

Some of the advantages of model based traffic flow prediction is that they are generic in which application even on routes with no detection equipment is possible, model based approaches allow to include different traffic control measures like traffic light, traffic information and also the models can provide full insight about the location and causes of delays on the road network of interest. Major disadvantages, however, include computational complexity, the degree of expertise required for design and maintenance, and influence of the inputs and boundary conditions on the quality of traffic flow prediction.

The other road traffic state estimation technique is data driven model. The basic difference between data driven and model based approach is that data driven approaches consider the road traffic process generating travel times as black box. These approaches include the parametric techniques ARIMA, Kalman filter, linear and support vector regression model, Time series model etc. and non-parametric methods like neural networks and various hybrid approaches for example neuro-fuzzy approaches or combination of different Artificial Neural Network topologies.

The clear advantages of data driven approaches are that they do not require extensive expertise on traffic flow modeling, they are fast and easy to implement, and specifically neural network approaches have proven accurate and reliable traffic predictors [88]. The major drawback of the data driven approaches including neural networks is that they are location specific, which means a solution that works well on one location may not work at all on the next.

In general, an elaborated discussion of model based and data driven approaches has been given with their advantages and disadvantages. Moreover, a comprehensive overview of existing urban short term road traffic state estimation approaches was presented. With the investigation made on the existing approaches, this dissertation adopts a hybrid method of combining artificial neural network (data driven) and model based approach to estimate urban road traffic flow condition.

References

[1] E. ARAYA, "New Third Party Insurance Elusive as Deadline Approaches," *Addis Fortune,* vol. 12, November 6 2011.

[2] J. Sousanis, "World Vehicle Population Tops 1 Billion Units," Ward Auto World, 2011.

[3] M. Juhel, "Safe Clean and Affordable Transport for Development: World Bank Business Strategy," in Presentation to the „Asia on the Move" Transport Forum Manila Philippines Sept, 2008.

[4] J. Vrancken and M. d. S. Soares, "Intelligent Road Network Control," Intelligent Infrastructures, pp. 311-325, 2010.

[5] K. Kyamakya, S. Fuchs, R. Koteswara, and J. Chedjou, "Road Traffic Tracking by using Location Management data in wireless cellular networks (TTLM)," ITG-Fachbericht-Mobilfunk, 2006.

[6] G. Leduc, "Road traffic data: Collection methods and applications," Working Papers on Energy, Transport and Climate Change, vol. 1, p. 55, 2008.

[7] P. T. Martin, Feng, Y. and Wang, X., "Detector technology evaluation," Mountain-Plains Consortium2003.

[8] A. Gühnemann, R.-P. Schäfer, K.-U. Thiessenhusen, and P. Wagner, "Monitoring traffic and emissions by floating car data," Institute of Transport Studies Working Paper, 2004.

[9] N. Caceres, J. Wideberg, and F. Benitez, "Review of traffic data estimations extracted from cellular networks," IET Intelligent Transport Systems, vol. 2, pp. 179-192, 2008.

[10] M. Khalaf-Allah and K. Kyamakya, "Tracking mobile terminals in wireless networks," in Waveform Diversity and Design Conference, 2007. International, 2007, pp. 46-49.

[11] P. Fiadino, D. Valerio, F. Ricciato, and K. A. Hummel, "Steps towards the extraction of vehicular mobility patterns from 3g signaling data," in Traffic Monitoring and Analysis, ed: Springer, 2012, pp. 66-80.

[12] S. Tao, S. Rodriguez, and A. Rusu, "Vehicle location using wireless wide area network," in Wireless and Mobile Networking Conference (WMNC), 2010 Third Joint IFIP, 2010, pp. 1-6.

[13] FCC, "FCC acts to promote competition and public safety in enhanced wireless 911 services," 1999.

[14] Y. Zhao, "Mobile phone location determination and its impact on intelligent transportation systems," Intelligent Transportation Systems, IEEE Transactions on, vol. 1, pp. 55-64, 2000.

[15] A.-K. V. Rongen, "The Necessity for an EU-wide 112 Emergency Wireless Location System," European Journal of Navigation, vol. 3, no. 4, pp. 32-35, 2005.

[16] 3GPP, "3GPP TS 22.071, Location Services (LCS); Service description; Stage 1 (Release 11)," 2012.

[17] T. Chew, "The Integration of Positioning Technologies for Precise Location Identification," 2005.

[18] K. Axel, "Location-Based Services: Fundamentals and Operation," John Wiely & Sons, 2005.

[19] S. Tao, V. Manolopoulos, S. Rodriguez, M. Ismail, and A. Rusu, "Hybrid vehicle positioning and tracking using mobile phones," in ITS Telecommunications (ITST), 2011 11th International Conference on, 2011, pp. 315-320.

[20] J. J. Caffery, Wireless location in CDMA cellular radio systems vol. 535: Kluwer Academic Pub, 2000.

[21] A. Bensky, Wireless positioning technologies and applications: Artech House, Inc., 2007.

[22] 3GPP, "3GPP TS 23.271 Technical Specification Functional stage 2 description of Location Services (LCS)," vol. 11, April 2013.

[23] 3GPP, "3GPP TS 43.059 Technical Specification Functional stage 2 description of Location Services (LCS) in GERAN," 11, April 2012.

[24] 3GPP, "3GPP TS 25.305 Technical Specification Stage 2 functional specification of User Equipment (UE) positioning in UTRAN," vol. 11, September 2012.

[25] Y. J. Guo, Advances in mobile radio access networks: Artech House Publishers, 2004.

[26] 3GPP, "3GPP TS 36.305 Technical Specification Stage 2 functional specification of User Equipment (UE) positioning in E-UTRAN," vol. 11, April 2013.

[27] I. K. Adusei, K. Kyamakya, and K. Jobmann, "Mobile positioning technologies in cellular networks: an evaluation of their performance metrics," in MILCOM 2002. Proceedings, 2002, pp. 1239-1244.

[28] T. Kos, M. Grgic, and G. Sisul, "Mobile user positioning in GSM/UMTS cellular networks," in Multimedia Signal Processing and Communications, 48th International Symposium ELMAR-2006 focused on, 2006, pp. 185-188.

[29] 3GPP, "3GPP Work Item Description:," May 2009.

[30] A. Clarkson, S. McCallum, N. Solhjoo, and S. Velentzas, "Hybridised Positioning Algorithms in Location Based Services."

[31] W. Lv, S. Ma, C. Liang, and T. Zhu, "Effective data identification in travel time estimation based on cellular network signaling," in Wireless and Mobile Networking Conference (WMNC), 2011 4th Joint IFIP, 2011, pp. 1-5.

[32] D. Gundlegard and J. M. Karlsson, "Route classification in travel time estimation based on cellular network signaling," in Intelligent Transportation Systems, 2009. ITSC'09. 12th International IEEE Conference on, 2009, pp. 1-6.

[33] C. W. Smith, I. Clayton Wilkinson, K. Carlson, M. P. Wright, and R. Sangal, "System and method for providing traffic information using operational data of a wireless network," ed: Google Patents, 2005.

[34] J. Kaplan and O. Avni, "Method for monitoring cellular communication, and system therefor," ed: Google Patents, 2005.

[35] Z. Sahinoglu and A. Vetro, "Mobility characteristics for multimedia service adaptation," Signal Processing: Image Communication, vol. 18, pp. 699-719, 2003.

[36] G. Limei and L. Dayong, "Apply Cellular Wireless Location Technologies to Traffic Information Gathering," in Proceedings of the 2009 Second International Conference on Intelligent Computation Technology and Automation-Volume 03, 2009, pp. 499-502.

[37] D. Gundlegård and J. M. Karlsson, "Road Traffic Estimation using Cellular Network Signaling in Intelligent Transportation Systems," 2009.

[38] A. Catovic and S. Tekinay, "Geolocation updating schemes for location aware services in wireless networks," in Military Communications Conference, 2001. MILCOM 2001. Communications for Network-Centric Operations: Creating the Information Force. IEEE, 2001, pp. 378-382.

[39] W.-J. Choi and S. Tekinay, "An adaptive location registration scheme with dynamic mobility classification," in Communications, 2002. ICC 2002. IEEE International Conference on, 2002, pp. 440-444.

[40] K. Puntumapon and W. Pattara-Atikom, "Classification of Cellular Phone Mobility using Naive Bayes Model," in Vehicular Technology Conference, 2008. VTC Spring 2008. IEEE, 2008, pp. 3021-3025.

[41] M. Ren, "Advanced Map Matching Technologies and Techniques for Pedestrian/Wheelchair Navigation," University of Pittsburgh, 2012.
[42] M. A. Quddus, R. B. Noland, and W. Y. Ochieng, "A high accuracy fuzzy logic based map matching algorithm for road transport," Journal of Intelligent Transportation Systems, vol. 10, pp. 103-115, 2006.
[43] W. Y. Ochieng, M. Quddus, and R. B. Noland, "Map-matching in complex urban road networks," Revista Brasileira de Cartografia, vol. 2, 2009.
[44] J. S. Greenfeld, "Matching GPS observations to locations on a digital map," in National Research Council (US). Transportation Research Board. Meeting (81st: 2002: Washington, DC). Preprint CD-ROM, 2002.
[45] D. Bernstein and A. Kornhauser, "An introduction to map matching for personal navigation assistants," 1996.
[46] M. A. Quddus, W. Y. Ochieng, and R. B. Noland, "Current map-matching algorithms for transport applications: State-of-the art and future research directions," Transportation Research Part C: Emerging Technologies, vol. 15, pp. 312-328, 2007.
[47] C. E. White, D. Bernstein, and A. L. Kornhauser, "Some map matching algorithms for personal navigation assistants," Transportation Research Part C: Emerging Technologies, vol. 8, pp. 91-108, 2000.
[48] D. Bernstein and A. Kornhauser, "Map matching for personal navigation assistants," In proceedings of the 77th annual meeting of the Transportation Research Board, 1998.
[49] Y. Meng, W. Chen, Z. Li, Y. Chen, and J. C. Chao, "A simplified map-matching algorithm for in-vehicle navigation unit," Geographic Information Sciences, vol. 8, pp. 24-30, 2002.
[50] N. R. Velaga, M. A. Quddus, and A. L. Bristow, "Developing an enhanced weight-based topological map-matching algorithm for intelligent transport systems," Transportation Research Part C: Emerging Technologies, vol. 17, pp. 672-683, 2009.
[51] G. Bishop and G. Welch, "An introduction to the kalman filter," Proc of SIGGRAPH, Course, vol. 8, pp. 27599-3175, 2001.
[52] F. Gustafsson, F. Gunnarsson, N. Bergman, U. Forssell, J. Jansson, R. Karlsson, and P.-J. Nordlund, "Particle filters for positioning, navigation, and tracking," Signal Processing, IEEE Transactions on, vol. 50, pp. 425-437, 2002.
[53] M. Negnevitsky, Artificial intelligence: a guide to intelligent systems: Pearson Education, 2005.
[54] P. Newson and J. Krumm, "Hidden markov map matching through noise and sparseness," in Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, 2009, pp. 336-343.
[55] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," Proceedings of the IEEE, vol. 77, pp. 257-286, 1989.
[56] S. V. Kumar, L. Vanajakshi, and S. C. Subramanian, "Traffic State Estimation and Prediction under Heterogeneous Traffic Conditions," 2011.
[57] J. Aydos, B. Hengst, W. Uther, A. Blair, and J. Zhang, "Stochastic Real-Time Urban Traffic State Estimation: Searching for the Most Likely Hypothesis with Limited and Heterogeneous Sensor Data," 2012.
[58] M. J. Lighthill and G. B. Whitham, "On kinematic waves. II. A theory of traffic flow on long crowded roads," Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences, vol. 229, pp. 317-345, 1955.
[59] N. H. Gartner, C. J. Messer, and A. K. Rathi, Traffic flow theory: A state-of-the-art report: Committe on Traffic Flow Theory and Characteristics (AHB45), 2001.
[60] S. Boubaker, F. Rehimi, and A. Kalboussi, "Comparative analysis of microscopic models of road traffic data," in Logistics (LOGISTIQUA), 2011 4th International Conference on, 2011, pp. 474-478.
[61] M. Van Aerde, B. Hellinga, M. Baker, and H. Rakha, "INTEGRATION: An overview of traffic simulation features," Transportation Research Records, 1996.
[62] I. Kosonen, HUTSIM-Urban traffic simulation and control model: principles and applications vol. 100, 1999.
[63] I. Quadstone, "The PARAMICS transportation modeling suite," URL= www. paramicsonline. com, Last Accessed Jan, vol. 19, 2011.
[64] M. Behrisch, L. Bieker, J. Erdmann, and D. Krajzewicz, "SUMO-Simulation of Urban MObility-an Overview," in SIMUL 2011, The Third International Conference on Advances in System Simulation, 2011, pp. 55-60.
[65] M. Fellendorf and P. Vortisch, "Validation of the microscopic traffic flow model VISSIM in different real-world situations," in National Research Council (US). Transportation Research Board. Meeting (80th: 2001: Washington, DC). Preprint CD-ROM, 2001.
[66] T. Toledo, H. N. Koutsopoulos, A. Davol, M. E. Ben-Akiva, W. Burghout, I. Andréasson, T. Johansson, and C. Lundin, "Calibration and validation of microscopic traffic simulation tools: Stockholm case study," Transportation Research Record: Journal of the Transportation Research Board, vol. 1831, pp. 65-75, 2003.
[67] S. Tao, V. Manolopoulos, S. Rodriguez Duenas, and A. Rusu, "Real-Time Urban Traffic State Estimation with A-GPS Mobile Phones as Probes," Journal of Transportation Technologies, vol. 2, pp. 22-31, 2012.
[68] H. Liu, H. van Lint, and H. van Zuylen, "Neural-Network-Based Traffic Flow Model for Urban Arterial Travel Time Prediction," in Transportation research board annual meeting, CD Rom, National Academies Press, Washington, DC, 2007.
[69] S. P. Hoogendoorn and P. H. Bovy, "State-of-the-art of vehicular traffic flow modelling," Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering, vol. 215, pp. 283-303, 2001.
[70] D. Yin and T. Z. Qiu, "Traffic jam modeling and simulation," in Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on, 2012, pp. 1423-1428.
[71] A. K. Ziliaskopoulos, S. T. Waller, Y. Li, and M. Byram, "Large-scale dynamic traffic assignment: Implementation issues and computational analysis," Journal of Transportation Engineering, vol. 130, pp. 585-593, 2004.
[72] W. Burghout, "Hybrid microscopic-mesoscopic traffic simulation," KTH, 2004.
[73] E. Bourrel and J.-B. Lesort, "Mixing microscopic and macroscopic representations of traffic flow: Hybrid model based on Lighthill-Whitham-Richards theory," Transportation Research Record: Journal of the Transportation Research Board, vol. 1852, pp. 193-200, 2003.
[74] X. Ma, W. Burghout, I. Andreasson, and H. N. Koutsopoulos, "Evaluation of Real-Time Travel Time Estimation Methods and Disruption Warning Using Noisy Automatic Vehicle Identification Measurements," in Transportation Research Board Annual Meeting 2009 Paper: Transportation Research Board 88th Annual Meeting, Washington DC, Jan. 2009, 2009.
[75] S. M. Turner, W. L. Eisele, R. J. Benz, and D. J. Holdener, "Travel time data collection handbook," 1998.
[76] T.-Y. Hu and W.-M. Ho, "Travel Time Prediction for Urban Networks: the Comparisons of Simulation-based and Time-Series Models," 2010.
[77] E. I. Vlahogianni, J. C. Golias, and M. G. Karlaftis, "Short□term traffic forecasting: Overview of objectives and methods," Transport reviews, vol. 24, pp. 533-557, 2004.
[78] V. Zeimpekis, "Design and evaluation of a real-time fleet management system for dynamic incident handling in urban

freight distribution," Athens University of Economics & Business, PhD Thesis, 2007.
[79] S. H. M. Lam and T. D. Toan, "Short-term travel time prediction using support vector regression," in Transportation Research Board 87th Annual Meeting, 2008.
[80] P. Cheng, Z. Qiu, and B. Ran, "Particle filter based traffic state estimation using cell phone network data," in Intelligent Transportation Systems Conference, 2006. ITSC'06. IEEE, 2006, pp. 1047-1052.
[81] J. Van Lint, "Online learning solutions for freeway travel time prediction," Intelligent Transportation Systems, IEEE Transactions on, vol. 9, pp. 38-47, 2008.
[82] L. Chu, S. Oh, and W. Recker, "Adaptive Kalman filter based freeway travel time estimation," in 84th TRB Annual Meeting, Washington DC, 2005.
[83] S. I.-J. Chien and C. M. Kuchipudi, "Dynamic travel time prediction with real-time and historic data," Journal of Transportation Engineering, vol. 129, pp. 608-616, 2003.
[84] M. Chen and S. I. Chien, "Dynamic freeway travel-time prediction with probe vehicle data: Link based versus path based," Transportation Research Record: Journal of the Transportation Research Board, vol. 1768, pp. 157-161, 2001.
[85] A. Stathopoulos and M. G. Karlaftis, "A multivariate state space approach for urban traffic flow modeling and prediction," Transportation Research Part C: Emerging Technologies, vol. 11, pp. 121-135, 2003.
[86] Y. Zhang and Y. Liu, "Comparison of Parametric and Nonparametric Techniques for Non-peak Traffic Forecasting," World Academy of Science, Engineering and Technology, vol. 51, 2009.
[87] H. van Lint, Reliable travel time prediction for freeways: Netherlands TRAIL Research School, 2004.
[88] S. C. Kremer, "Spatiotemporal Connectionist Networks: A Taxonomy and."
[89] H. Liu, K. Zhang, R. He, and J. Li, "A neural network model for travel time prediction," in Intelligent Computing and Intelligent Systems, 2009. ICIS 2009. IEEE International Conference on, 2009, pp. 752-756.
[90] J. You and T. J. Kim, "Development and evaluation of a hybrid travel time forecasting model," Transportation Research Part C: Emerging Technologies, vol. 8, pp. 231-256, 2000.
[91] J. Anderson and M. Bell, "Travel time estimation in urban road networks," in Intelligent Transportation System, 1997. ITSC'97., IEEE Conference on, 1997, pp. 924-929.
[92] A. H. Sayed, A. Tarighat, and N. Khajehnouri, "Network-based wireless location: challenges faced in developing techniques for accurate wireless location information," Signal Processing Magazine, IEEE, vol. 22, pp. 24-40, 2005.
[93] S. Al-Jazzar, M. Ghogho, and D. McLernon, "A joint TOA/AOA constrained minimization method for locating wireless devices in non-line-of-sight environment," Vehicular Technology, IEEE Transactions on, vol. 58, pp. 468-472, 2009.
[94] C. Guangqian, L. Zuowei, W. Xiaohong, S. Shiying, and H. Jianwen, "Research on TDOA/AOA hybrid positioning system based on Kalman filtering," in Signal Processing Systems (ICSPS), 2010 2nd International Conference on, 2010, pp. V2-720-V2-723.
[95] R. Mardeni, P. Shahabi, and M. Riahimanesh, "Mobile station localization in wireless cellular systems using UTDOA," in Microwave and Millimeter Wave Technology (ICMMT), 2012 International Conference on, 2012, pp. 1-4.
[96] J. Borkowski and J. Lempiäinen, "Pilot correlation positioning method for urban UMTS networks," in Wireless Conference 2005-Next Generation Wireless and Mobile Communications and Services (European Wireless), 11th European, 2005, pp. 1-5.
[97] B. Jakub, "Practical Network-Based Techniques for Mobile Positioning in UMTS," EURASIP Journal on Advances in Signal Processing, vol. 2006, 2006.
[98] D. Bartlett, Essentials of Positioning and Location Technology: Cambridge University Press, 2013.
[99] H. Kunczier and H. Anegg, "Enhanced cell ID based terminal location for urban area location based applications," in Consumer Communications and Networking Conference, 2004. CCNC 2004. First IEEE, 2004, pp. 595-599.
[100] E. Trevisani and A. Vitaletti, "Cell-ID location technique, limits and benefits: an experimental study," in Mobile Computing Systems and Applications, 2004. WMCSA 2004. Sixth IEEE Workshop on, 2004, pp. 51-60.
[101] P. Duffett-Smith and M. Macnaughtan, "Precise UE positioning in UMTS using cumulative virtual blanking," in 3G Mobile Communication Technologies, 2002. Third International Conference on (Conf. Publ. No. 489), 2002, pp. 355-359.
[102] D. Bartlett, "Software blanking for OTDOA positioning," in Proceedings of the, 2002, pp. 1-7.
[103] S. Ahonen and P. Eskelinen, "Mobile terminal location for UMTS," Aerospace and Electronic Systems Magazine, IEEE, vol. 18, pp. 23-27, 2003.
[104] S. Ahonen and H. Laitinen, "Database correlation method for UMTS location," in Vehicular Technology Conference, 2003. VTC 2003-Spring. The 57th IEEE Semiannual, 2003, pp. 2696-2700.
[105] K. Singh and M. Ismail, "OTDOA location determining technology for universal intelligent positioning system (UIPS) implementation in Malaysia," in Networks, 2005. Jointly held with the 2005 IEEE 7th Malaysia International Conference on Communication., 2005 13th IEEE International Conference on, 2005, p. 5 pp.
[106] D. Porcino, "Performance of a OTDOA-IPDL positioning receiver for 3GPP-FDD mode," 2001.
[107] G. M. Djuknic and R. E. Richton, "Geolocation and assisted GPS," Computer, vol. 34, pp. 123-125, 2001.
[108] B. Richton, G. Vanucci, and S. Wilkus, "Assisted GPS for Wireless Phone Location-Technology and Standards," KLUWER INTERNATIONAL SERIES IN ENGINEERING AND COMPUTER SCIENCE, pp. 129-156, 2001.
[109] M. Abo-Zahhad, S. M. Ahmed, and M. Mourad, "Hybrid Uplink-Time Difference of Arrival and Assisted-GPS Positioning Technique," International Journal of Communications, Network and System Sciences, vol. 5, 2012.
[110] D. Drakoulis, S. Kyriazakos, and G. Karetsos, "Improving subscriber position location using a hybrid satellite-assisted and network-based technique," in Vehicular Technology Conference, 2000. IEEE VTS-Fall VTC 2000. 52nd, 2000, pp. 1887-1893.
[111] H. C. Son, J. G. Lee, and G. I. Jee, "Mobile station location using hybrid GPS and a wireless network," in Vehicular Technology Conference, 2003. VTC 2003-Spring. The 57th IEEE Semiannual, 2003, pp. 2716-2720.
[112] A. Broumandan, T. Lin, J. Nielsen, and G. Lachapelle, "Practical results of hybrid AOA/TDOA geo-location estimation in CDMA wireless networks," in Vehicular Technology Conference, 2008. VTC 2008-Fall. IEEE 68th, 2008, pp. 1-5.
[113] C.-L. Chen and K.-T. Feng, "Hybrid location estimation and tracking system for mobile devices," in Vehicular Technology Conference, 2005. VTC 2005-Spring. 2005 IEEE 61st, 2005, pp. 2648-2652.
[114] J. Chen and A. Abedi, "A Hybrid Framework for Radio Localization in Broadband Wireless Systems," in Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE, 2010, pp. 1-6.
[115] J. Borkowski, J. Niemela, and J. Lempiainen, "Cellular location techniques supporting AGPS positioning," in IEEE VEHICULAR TECHNOLOGY CONFERENCE, 2005, p. 429.

[116] M. A. Quddus, "High integrity map matching algorithms for advanced transport telematics applications," Imperial College London, United Kingdom, 2006.
[117] D. Srinivasan, R. L. Cheu, and C. W. Tan, "Development of an improved ERP system using GPS and AI techniques," in Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE, 2003, pp. 554-559.
[118] A. Bouju, A. Stockus, R. Bertrand, and P. Boursier, "Location-based spatial data management in navigation systems," in Intelligent Vehicle Symposium, 2002. IEEE, 2002, pp. 172-177.
[119] S. Mahajan and Y. Singh, "Enhanced mobile station localization using a hybrid TOA/AOA map-matching algorithm," in TENCON 2009-2009 IEEE Region 10 Conference, 2009, pp. 1-6.
[120] M. A. Quddus, W. Y. Ochieng, L. Zhao, and R. B. Noland, "A general map matching algorithm for transport telematics applications," GPS solutions, vol. 7, pp. 157-167, 2003.
[121] Z. Wang and Z. Yang, "Research on the Map Matching of Typical Region Based on the Topological Analysis," in Intelligent Computation Technology and Automation, 2009. ICICTA'09. Second International Conference on, 2009, pp. 629-632.
[122] C. A. Blazquez, "A Decision-Rule Topological Map-Matching Algorithm with Multiple Spatial Data."
[123] W. Kim, G.-I. Jee, and J. Lee, "Efficient use of digital road map in various positioning for ITS," in Position Location and Navigation Symposium, IEEE 2000, 2000, pp. 170-176.
[124] H. Xu, H. Liu, C.-W. Tan, and Y. Bao, "Development and application of an enhanced kalman filter and global positioning system error-correction approach for improved map-matching," Journal of Intelligent Transportation Systems, vol. 14, pp. 27-36, 2010.
[125] D. Yang, B. Cai, and Y. Yuan, "An improved map-matching algorithm used in vehicle navigation system," in Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE, 2003, pp. 1246-1250.
[126] M. Fu, J. Li, and M. Wang, "A hybrid map matching algorithm based on fuzzy comprehensive Judgment," in Intelligent Transportation Systems, 2004. Proceedings. The 7th International IEEE Conference on, 2004, pp. 613-617.
[127] Y. Zhang and Y. Gao, "A fuzzy logic map matching algorithm," in Fuzzy Systems and Knowledge Discovery, 2008. FSKD'08. Fifth International Conference on, 2008, pp. 132-136.
[128] G. Jagadeesh, T. Srikanthan, and X. Zhang, "A map matching method for GPS based real-time vehicle location," Journal of Navigation, vol. 57, pp. 429-440, 2004.
[129] Y.-L. Yang, H. Ye, and S.-M. Fei, "Integrated map-matching algorithm based on fuzzy logic and dead reckoning," in Control Automation and Systems (ICCAS), 2010 International Conference on, 2010, pp. 1139-1142.
[130] R. Toledo-Moreo, D. Bétaille, and F. Peyret, "Lane-level integrity provision for navigation and map matching with GNSS, dead reckoning, and enhanced maps," Intelligent Transportation Systems, IEEE Transactions on, vol. 11, pp. 100-112, 2010.
[131] P. Davidson, J. Collin, and J. Takala, "Application of particle filters to a map-matching algorithm," Gyroscopy and Navigation, vol. 2, pp. 285-292, 2011.
[132] Z. Chen, "Bayesian filtering: From Kalman filters to particle filters, and beyond," Statistics, vol. 182, pp. 1-69, 2003.
[133] D. Crisan and A. Doucet, "A survey of convergence results on particle filtering methods for practitioners," Signal Processing, IEEE Transactions on, vol. 50, pp. 736-746, 2002.
[134] L. Xue, S. Gao, and G. Hu, "Proposed robust auxiliary particle filtering for navigation system," in Mechatronics and Automation (ICMA), 2012 International Conference on, 2012, pp. 511-515.
[135] S. Kim and J.-H. Kim, "Adaptive fuzzy-network-based C-measure map-matching algorithm for car navigation system," Industrial Electronics, IEEE Transactions on, vol. 48, pp. 432-441, 2001.
[136] S. Syed and M. Cannon, "Fuzzy logic-based map matching algorithm for vehicle navigation system in urban canyons," in proceedings of the Institute of Navigation (ION) national technical meeting, USA, 2004.
[137] G. Li-mei and L. Da-yong, "Development of a Integrated Map Matching Algorithm Based on Fuzzy Theory," in Intelligent Computation Technology and Automation, 2009. ICICTA'09. Second International Conference on, 2009, pp. 693-696.
[138] R. Raymond, T. Morimura, T. Osogami, and N. Hirosue, "Map matching with hidden markov model on sampled road network," in Pattern Recognition (ICPR), 2012 21st International Conference on, 2012, pp. 2242-2245.
[139] C. Goh, J. Dauwels, N. Mitrovic, M. Asif, A. Oran, and P. Jaillet, "Online map-matching based on Hidden Markov model for real-time traffic sensing applications," in Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on, 2012, pp. 776-781.
[140] Y. Kamarianakis and P. Prastacos, "Forecasting traffic flow conditions in an urban network: comparison of multivariate and univariate approaches," Transportation Research Record: Journal of the Transportation Research Board, vol. 1857, pp. 74-84, 2003.
[141] S. Clark, "Traffic prediction using multivariate nonparametric regression," Journal of Transportation Engineering, vol. 129, pp. 161-168, 2003.
[142] J.-S. Yang, "Travel time prediction using the GPS test vehicle and Kalman filtering techniques," in American Control Conference, 2005. Proceedings of the 2005, 2005, pp. 2128-2133.
[143] M. Vasudevan and K. E. Wunderlich, "A neural network approach to constructing commercial broadcast traffic advisories," in Intelligent Transportation Systems, 2004. Proceedings. The 7th International IEEE Conference on, 2004, pp. 791-796.
[144] F. Batool and S. A. Khan, "Traffic estimation and real time prediction using adhoc networks," in Emerging Technologies, 2005. Proceedings of the IEEE Symposium on, 2005, pp. 264-269.
[145] A. Guin, "Travel time prediction using a seasonal autoregressive integrated moving average time series model," in Intelligent Transportation Systems Conference, 2006. ITSC'06. IEEE, 2006, pp. 493-498.
[146] H. Liu, H. Van Lint, H. Van Zuylen, and K. Zhang, "Two distinct ways of using Kalman filters to predict urban arterial travel time," in Intelligent Transportation Systems Conference, 2006. ITSC'06. IEEE, 2006, pp. 845-850.
[147] C. De Fabritiis, R. Ragona, and G. Valenti, "Traffic estimation and prediction based on real time floating car data," in Intelligent Transportation Systems, 2008. ITSC 2008. 11th International IEEE Conference on, 2008, pp. 197-203.
[148] T. Zhu, X. Kong, and W. Lv, "Large-scale travel time prediction for urban arterial roads based on Kalman filter," in Computational Intelligence and Software Engineering, 2009. CiSE 2009. International Conference on, 2009, pp. 1-5.
[149] H. Dong, L. Jia, X. Sun, C. Li, and Y. Qin, "Road traffic flow prediction with a time-oriented ARIMA model," in INC, IMS and IDC, 2009. NCM'09. Fifth International Joint Conference on, 2009, pp. 1649-1652.
[150] L. Wei, Z. Fang, and S. Luan, "Travel time prediction method for urban expressway link based on artificial neural network," in Natural Computation, 2009. ICNC'09. Fifth International Conference on, 2009, pp. 358-362.
[151] D. Chen, K. Zhang, and T. Liao, "Practical travel time prediction algorithms based on neural network and data fusion

for urban expressway," in Natural Computation (ICNC), 2010 Sixth International Conference on, 2010, pp. 1754-1758.
[152] C. van Hinsbergen, A. Hegyi, J. van Lint, and H. van Zuylen, "Bayesian neural networks for the prediction of stochastic travel times in urban networks," IET Intelligent Transport Systems, vol. 5, pp. 259-265, 2011.
[153] J. Wang, K. Wong, and Y. Chen, "Short-term travel time estimation and prediction for long freeway corridor using NN and regression," in Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on, 2012, pp. 582-587.
[154] J. Yang, Chou, L., Tung, C., Huang, S. and Wang, T., "Average Speed Forecast and Adjustment via VANETs," IEEE, 2013.
[155] H. Zhang, "Recursive prediction of traffic conditions with neural network models," Journal of Transportation Engineering, vol. 126, pp. 472-481, 2000.
[156] C. Wei, S. Lin, and Y. Li, "Empirical Validation of Freeway Bus Travel Time Forecasting," Transportation Planning Journal, vol. 32, pp. 651-679, 2003.
[157] L. Kisgyörgy and L. R. Rilett, "Travel time prediction by advanced neural network," Civil Engineering, vol. 46, pp. 15-32, 2002.
[158] S. Ishak and C. Alecsandru, "Optimizing traffic prediction performance of neural networks under various topological, input, and traffic condition settings," Journal of Transportation Engineering, vol. 130, pp. 452-465, 2004.
[159] H. Yin, S. Wong, J. Xu, and C. Wong, "Urban traffic flow prediction using a fuzzy-neural approach," Transportation Research Part C: Emerging Technologies, vol. 10, pp. 85-98, 2002.
[160] C. Alecsandru and S. Ishak, "Hybrid model-based and memory-based traffic prediction system," Transportation Research Record: Journal of the Transportation Research Board, vol. 1879, pp. 59-70, 2004.
[161] W. Zheng, D.-H. Lee, and Q. Shi, "Short-term freeway traffic flow prediction: Bayesian combined neural network approach," Journal of Transportation Engineering, vol. 132, pp. 114-121, 2006.
[162] J. W. van Lint, S. Hoogendoorn, and H. J. van Zuylen, "Freeway travel time prediction with state-space neural networks: Modeling state-space dynamics with recurrent neural networks," Transportation Research Record: Journal of the Transportation Research Board, vol. 1811, pp. 30-39, 2002.
[163] C. Solbé, "3G/UMTS family welcomes its 500 millionth customer," UMTS Forum, January 28 2010.
[164] N. Lomas, "ABI: Africa's Mobile Market To Pass 80% Subscriber Penetration In Q1 Next Year; 13.9% Of Global Cellular Market By 2017," November 2012.
[165] Dailyeurope, "Ethio-telecom to scrap 3G for LTE," Dailyeurope, March 2013.
[166] M. Tekleberhan, "Ethiopia's Telecom Re-Launches 3G Network," May 2012.
[167] P. Mohan, V. N. Padmanabhan, and R. Ramjee, "Nericell: rich monitoring of road and traffic conditions using mobile smartphones," in Proceedings of the 6th ACM conference on Embedded network sensor systems, 2008, pp. 323-336.
[168] P.-H. Tseng and K.-T. Feng, "Hybrid Network/satellite-based location estimation and tracking systems for wireless networks," Vehicular Technology, IEEE Transactions on, vol. 58, pp. 5174-5189, 2009.
[169] Q. Huang and J. Liu, "Mobile Tracking Using Hybrid Measurements in NLOS Environments," in ITS Telecommunications Proceedings, 2006 6th International Conference on, 2006, pp. 1075-1078.
[170] C. Drane, M. Macnaughtan, and C. Scott, "Positioning GSM telephones," Communications Magazine, IEEE, vol. 36, pp. 46-54, 59, 1998.
[171] Canalys, "Mobile device market to reach 2.6 billion units by 2016," Febrary 2013.
[172] W. S. S. W. service, "Africa Smartphone Sales Will Jump 56% in 2013 " 2013.
[173] I. N. AFRICA, "Ethiopia to assemble their first smartphone," June 2012.
[174] H. Zhang, "The optimality of naive Bayes," A A, vol. 1, p. 3, 2004.
[175] B.-S. Chen, C.-Y. Yang, F.-K. Liao, and J.-F. Liao, "Mobile location estimator in a rough wireless environment using extended Kalman-based IMM and data fusion," Vehicular Technology, IEEE Transactions on, vol. 58, pp. 1157-1169, 2009.