Traffic Information Estimation Methods Based on Cellular Network Data

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By

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Cambridge Scholars Publishing

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This book first published 2023

Cambridge Scholars Publishing

Lady Stephenson Library, Newcastle upon Tyne, NE6 2PA, UK

British Library Cataloguing in Publication Data
A catalogue record for this book is available from the British Library

ISBN (10): 1-5275-3112-0
ISBN (13): 978-1-5275-3112-3

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ABSTRACT

The quality of Intelligent Transportation Systems (ITS) has been enhanced by advancements in information and communication technologies. The use of Cellular Floating Vehicle Data (CFVD) for vehicle speed estimation is comparatively more cost-effective and easier to obtain than traditional methods. In this study, three vehicle speed estimation methods have been proposed - Handover (HO)-based, Fingerprint Positioning Algorithm (FPA)-based, and Cell Probe (CP)-based methods, which analyze the cellular network signalings. Additionally, analytical models have been proposed to assess the correlation between cellular network signalings (such as received signal strength indication, call arrival, HO, normal location update, and periodic location update) and traffic information (such as traffic flow, traffic density, and vehicle speed). In the experiments conducted in this study, the estimated traffic information obtained by the proposed methods was compared to the real traffic information of vehicle detector. The results of the experiments revealed that the CP-based method had the highest accuracy of vehicle speed estimation, with a rate of 97.48%, as compared to the HO-based and FPA-based methods. Therefore, the CP-based method is recommended for the estimation of vehicle speed from CFVD for ITS.

Keywords: Intelligent Transportation System, Cellular Network, Traffic Flow Estimation, Traffic Density Estimation, Vehicle Speed Estimation

PREFACE

This book includes five chapters, and each chapter has been introduced in the following paragraphs.

Chapter 1: This chapter illustrates the research background and objectives of traffic information estimation methods based on cellular network data. It discusses and highlights the advantages and limitations of different data source categories for traffic information estimation, such as Vehicle Detector (VD), Global Position System (GPS)-based probe car reporting, and Cellular Floating Vehicle Data (CFVD).

Chapter 2: The literature reviews of the relevant systems and methods for Intelligent Transportation Systems (ITS) have been investigated. This book focuses on CFVD-based traffic information estimation, so the architecture and mechanisms of cellular networks have been described in this chapter. The signals including Call Arrival (CA), Handover (HO), Normal Location Update (NLU), and Periodical Location Update (PLU) are defined and explained.

Chapter 3: This chapter proposes three traffic information estimation methods: HO-based, Fingerprint Positioning Algorithm (FPA)-based, and Cell Probe (CP)-based methods. Analytical mathematical models have been proposed and demonstrated to analyze these methods. The proposed methods can estimate real-time traffic information by analyzing Received Signal Strengths (RSS) and signals such as Call Arrival (CA), Handover (HO), Normal Location Update (NLU), and Periodical Location Update (PLU) events.

Chapter 4: In Chapter 4, practical traffic data collected from the Ministry of Transportation & Communications (MOTC) in Taiwan, and practical cellular network signals from Chunghwa Telecom Co., Ltd. are analyzed to evaluate the proposed methods. The experimental results demonstrate that the proposed methods can obtain precise estimates of traffic information for Intelligent Transportation Systems (ITS).

Chapter 5: This chapter concludes the contributions of the author's findings in this book and discusses future work on traffic information estimation methods based on cellular network data.

The author would like to express gratitude to Cambridge Scholars Publishing and Chunghwa Telecom Co., Ltd. for their great support and assistance.

Abel C. H. Chen
Chunghwa Telecom Co., Ltd., Taiwan
15 March 2023

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CHAPTER 1

INTRODUCTION

1.1 Research Background

The demand for Intelligent Transportation Systems (ITS) for traffic services has increased with the recent rise in economic growth and technological advancements. The construction of real-time traffic information systems for ITS has become increasingly important. Real-time traffic information, such as average vehicle speed, travel time, traffic flow, and traffic congestion, can be referenced by road users and the ministry of transportation to improve the level of service for roadways. Consequently, many research articles have been published to improve traffic information services.

According to recent research, methods for collecting real-time traffic information can be categorized into three groups: Vehicle Detector (VD), Global Position System (GPS)-based probe car reporting, and Cellular Floating Vehicle Data (CFVD). The traditional method for gathering traffic information has been through public agencies (Departments of Transportation) using stationary VDs installed in the roadways to detect average vehicle speed and traffic flow. However, the installation and maintenance of such devices can be quite costly. An alternative approach is to collect traffic information from travelling vehicles equipped with GPS receivers and wireless communication capabilities as probes on the road network. However, the penetration rate of GPS-based probe cars needs to be high enough to infer more accurate real-time traffic information.

The third method, CFVD, which collects and detects real-time traffic information by tracking the location of Mobile Stations (MSs) through cellular network signaling (e.g., Normal Location Update (NLU), Periodic Location Update (PLU), Call Arrival (CA), and Handover (HO)), is becoming increasingly popular for ITS. For example, ITIS Holdings, a leading European traffic information company, applies patented CFVD technology to measure and forecast real-time traffic information based on anonymously sampling the positions of MSs (Logghe & Maerivoet, 2007). Therefore, CFVD is cost-effective, immediate, and easy to maintain. As the number of people owning cell phones has increased, using MSs as probes for obtaining traffic information has become more feasible.

In order to ensure the quality of service, cellular networks have established strict management processes to track the movement of Mobile Stations (MSs). Mobility management triggers control signal events such as Location Update (LU). Location Areas (LAs) can be defined by grouping cells to describe the high-level location information of MSs. When a MS moves from one LA to another, a NLU event is triggered to inform the cellular network of the MS's latest LA information via a specific cell. The message content includes the MS ID (i.e., International Mobile Subscriber Identity (IMSI)), LA Identifier (LAI), Cell Identity (CI), timestamp, and the reason for the update. For example, Caceres et al. use location update events as a "virtual traffic counter" to monitor the passage of phones through two LAs to measure traffic flow (Caceres et al., 2007; Caceres et al., 2008).

Furthermore, some studies have analyzed the relationship between the amount of cellular calls and traffic density. INRETS developed a study that detected changes in call volume and linked them to the occurrence of incidents (Ygnace, 2001). Ratti et al. reported that the amount of phone calls is closely linked to vehicular density by analyzing the real data they collected (Ratti et al., 2006). However, the accurate estimation of traffic density from cell phone probe data has not been investigated.

For vehicle speed estimation, Lin et al. proposed a Fingerprint Positioning Algorithm (FPA) to analyze the location and vehicle speed of MSs with measurement reports (Lin et al., 2011b; Chen et al., 2012a; Chen et al., 2012b). Gundlegard and Karlsson analyzed vehicle speed estimation accuracies based on handover locations (Gundlegard & Karlsson, 2009). While these approaches provide higher location determination accuracy, analyzing each measurement report requires higher power consumption.

1.2 Motivation

This study proposes several analytic models for estimating traffic flow and density based on cellular network data. Specifically, the proposed models use the number of NLUs and HOs to estimate traffic flow and the number of PLUs and CAs to estimate traffic density. The study also introduces the Cell Probe (CP) method, which leverages the estimated traffic flow and density to estimate vehicle speed. The three methods for estimating vehicle speed, namely the HO-based method, FPA-based method, and CP-based method, are compared and analyzed. Simulation results demonstrate the feasibility of the proposed approach.

1.3 Book Structure

The book is structured as follows: Chapter 2 provides background information on the collection of traffic information from cellular networks. In Chapter 3, the proposed vehicle speed estimation models from CFVD are presented, and a numerical analysis of the proposed model is provided. Chapter 4 illustrates the experiment results and analyses. Finally, Chapter 5 concludes the book.

CHAPTER 2

LITERATURE REVIEW

The following subsections provide an overview of the necessary research background and relevant technology, including Intelligent Transportation System (ITS), cellular networks, and traffic information collection.

2.1 Intelligent Transportation System

Intelligent Transportation Systems provide accurate and reliable real-time traffic information to road users and traffic managers, such as vehicle speed and flow, travel time, and accident events. This real-time traffic information supports on-vehicle navigation systems, vehicle dispatch systems, and traffic control. Recent research has indicated that real-time traffic information can be collected through three methods: VD, GPS-based probe cars reporting, and CFVD.

2.1.1 Vehicle Detector

Traditionally, traffic information has been gathered by public agencies such as Departments of Transportation through stationary Vehicle Detectors installed on roadways. The most common stationary Vehicle Detectors are inductive loops installed in roadbeds. Other Vehicle Detector technologies, such as active infrared/laser, magnetic, radar, and video, have also been developed (Martin et al., 2003; Minge et al., 2010). Each Vehicle Detector requires a communications link back to the Traffic Information Center (TIC). However, stationary Vehicle Detectors are expensive to install, operate, and maintain. Additionally, the operation of Vehicle Detectors may be limited by environmental conditions (shown in Table 1). For example, inductive loops have high failure rates due to exposure to extreme temperatures (Martin et al., 2003). Therefore, Vehicle Detector installations are typically limited to freeway or highway surveillance. However, the deployment cost of Vehicle Detectors along

Highway No. 1 in Taiwan was estimated to be over $2,276,200 for every kilometer with 760 Vehicle Detectors (Lin, 2011).

Table. 1. The comparison of VD technologies (Martin et al., 2003; Minge et al., 2010)

Device	**Technology**	**Operation**	**Limitations**	**Cost**
PEEK AxleLight	Laser	The corresponding reduction in time for the signal return is used to measure and detect the vehicle.	The sensors are limited by the dirt and road-grime on the lens and inclement weather.	$31,580
Wavetronix SmartSensor HD	Radar	The frequency-modulated or phase-modulated signal is used to be determined the time delay of the return signal for vehicle detection.	The detection quality may be affected by environmental conditions (e.g., barriers, fencing, or other obstructions).	$6,500
GTT Canoga Microloop	Magnetometer	This technique can detect perturbations in the Earth's magnetic field caused by the metallic components of vehicles.	For sensor installation, sensors that mount beneath the pavement require directional conduit boring.	$4,000
Miovision	Video	A microprocessor analyzes the the video image input to detect the vehicle and to generate traffic information.	The video image quality may be affected by environmental conditions (e.g., fog, rain, dust or snow).	$2,995 The video analysis is needed to be extra charged.

2.1.2 Global Position System-Based Probe Car Reporting

An alternative way to gather traffic information is to use GPS-equipped vehicles with wireless communication capabilities as probes on the road network. These probe cars periodically transmit their positions and speeds to a TIC. Taxis are commonly chosen as probe cars since they are more likely to be in constant motion (Martin et al., 2003). For instance, San Francisco taxis have been utilized as probes to collect and forecast traffic conditions (Hunter et al., 2009). Although the GPS receivers and wireless communication devices are moderately expensive, a significant number of probe cars must be equipped to ensure that enough data is collected to generate real-time traffic information for a large road network. Herrera et al. conducted a study on traffic data obtained from 100 vehicles carrying GPS-enabled mobile phones driving loops on a highway (Herrera et al., 2010). The vehicles recorded their speeds and locations when passing predetermined locations. Their study suggests that a 2-3% penetration of probe cars is sufficient to provide accurate measurements of vehicle speed.

2.1.3 Cellular Floating Vehicle Data

Nowadays, cellular phones or mobile stations (MSs) are ubiquitous. Due to their constant registration of locations to the cellular network, MSs on moving vehicles can be leveraged as probes to collect traffic information. This method is commonly known as CFVD, where real-time traffic information is inferred from cellular network signalings (Thiessenhusen et al., 2003; Bar-Gera, 2007; Logghe & Maerivoet, 2007; Gundlegard & Karlsson, 2009). In a cellular network, the service area is composed of Base Stations (BSs), where a BS or a sector of a BS's radio coverage is defined as a cell. When an MS is communicating and moves from one cell to another, a handover procedure is executed to allow the call to continue. By performing two consecutive handovers, the vehicle's speed can be estimated based on the distance between the two handover locations and the time difference of the two handovers. Compared to traditional probe vehicles, the CFVD approach does not necessitate additional on-vehicle equipment, and probes are abundant due to the widespread usage of MSs.

Several research projects have explored the use of CFVD, which utilizes two consecutive handover signalings from the cellular network to estimate vehicle speed and travel time. Gundlegard and Karlsson demonstrated high accuracy in localizing handover locations on both Global System for Mobile Communications (GSM) and Universal Mobile Telecommunications System (UMTS) networks, with UMTS providing more accurate speed estimation than GSM (Gundlegard & Karlsson, 2009). Thiessenhusen et al. compared vehicle speeds obtained from two consecutive handover records of GSM with those obtained from stationary VDs and GPS-equipped probe cars, and found errors between 20 to 30 km/h (Thiessenhusen et al., 2003). Meanwhile, Maerivoet and Logghe showed that CFVD technology had very good accuracy on motorways with free-flow traffic (Logghe & Maerivoet, 2007). Bar-Gera's CFVD study demonstrated that the discrepancy between travel times obtained from stationary VDs and CFVD is on average 10.7% (Bar-Gera, 2007).

The above-mentioned studies indicate that CFVD can be useful in estimating vehicle speed and travel time. However, during traffic congestion, consecutive handover events are rare, resulting in very few speed reports from CFVD. Although CFVD can indicate the presence of a traffic jam due to the lack of speed reports, it cannot determine the severity of the congestion. This issue has not been thoroughly investigated in the literature. Therefore, this paper presents an analytic model to estimate the speed report rate of CFVD under steady traffic conditions. Real anonymized signaling traces from a cellular network are used to validate our analytic model. In addition, computer simulations are conducted to determine whether CFVD can generate speed reports when traffic becomes congested rapidly due to a traffic accident.

2.2 Cellular Networks

Figure 1 shows the network architecture of the GSM/General Packet Radio Service (GPRS)/UMTS systems. The solid lines in the figure indicate data and signaling links, while the dashed lines indicate signaling links only (Lin & Pang, 2005). The following section describes the components and Mobility Management (MM) in cellular networks.

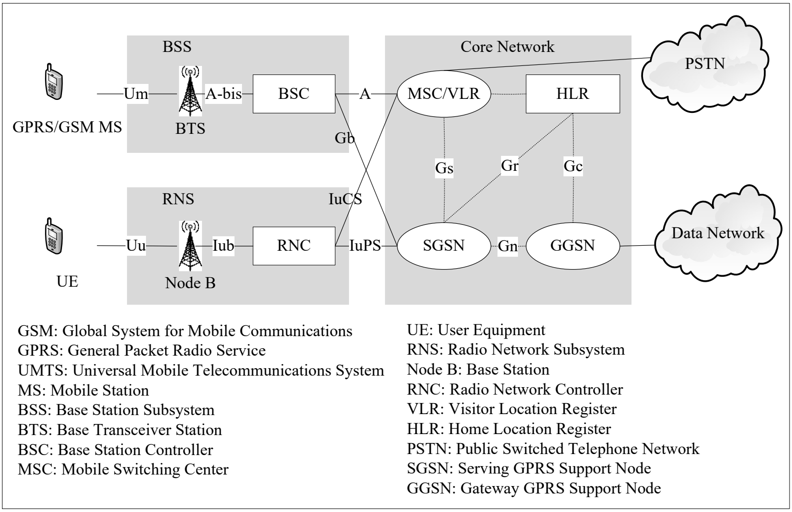

Figure. 1. The architecture of cellular networks
(Lin & Pang, 2005)

2.2.1 System Components

The GSM is a network that includes several components, including Mobile Stations (MS), Base Transceiver Stations (BTS), Base Station Controllers (BSC), Mobile Switching Centers (MSC), Home Location Registers (HLR), and Visitor Location Registers (VLR) (Lin & Pang, 2005). MSs communicate with the network via the A-bis interface through BTS and BSC. The BSC communicates with the MSC via the A interface, which can connect calls from the MSs to the Public Switched Telephone Network (PSTN). HLR and VLR provide mobility management and store location information of MSs.

GPRS, an evolution of GSM, added Serving GPRS Support Node (SGSN) and Gateway GPRS Support Node (GGSN) to establish data connections with the internet (Lin & Pang, 2005). However, this study focuses on circuit-switched networks, and packet-switched networks' signalings are not discussed or analyzed.

UMTS adds User Equipment (UE), Node B, Radio Network Controller (RNC), and the components in GSM and GPRS to the network (Lin & Pang, 2005). UEs communicate with the network via the Iub interface through Node B and RNC. The BSC communicates with the MSC via the IuCS interface, which can connect calls from the UEs to the PSTN.

2.2.2 Mobility Management

Regarding MM, the functions related to the management of common transmission resources can be carried out according to the MS/UE. RR management includes two modes: idle mode and Radio Resource (RR) connected mode.

2.2.2.1 Idle Mode

In idle mode, MM performs the location updating procedures. This is a general procedure that is used for the following purposes (ETSI, 1995):

(1). Normal Location Updating (NLU) - performed when a new location area is entered.
(2). Periodic Location Updating (PLU) - performed when a timer expires.
(3). IMSI Attach - performed when the MS is turned on.

2.2.2.2 Radio Resource Connected Mode

In RR connected mode, handover procedures are performed for MM. MSC can control the call and the MM of the MS during the call. When the MS enters a new cell during a call, the handover procedure is performed to provide good quality of RR by MSC (ETSI, 1997).

2.3 Traffic Information Collection in Accordance with Cellular Network Signalings

The traffic information in recent years can be linked to the number of MSs and network signaling. Various methods have been proposed to gather mobility and location data from cellular networks, primarily to estimate real-time traffic information for LU, Routing Area Update (RAU), and HO.

These methods can be classified into three groups: (1) monitoring the amount of network signaling from control channels, (2) using mobile positioning algorithms to estimate speed, and (3) using handover information to estimate speed.

2.3.1 Monitoring Control Channel

The MS initiates LU/RAU upon entering a different LA/RA, even in idle mode. CA events, HO events, and call departure (CD) events are triggered when a MS initiates a call. Some studies have utilized these network signalings (i.e., LU, RAU, CA, HO, and CD) from control channels to estimate the number of MSs on a specific road segment covered by a cell and compare it with previous data to detect abnormal traffic conditions (Caceres et al., 2007; Caceres et al., 2008). This section includes two discussions: (1) the method of collecting and counting LU/RAU to estimate traffic flow and accidents and (2) the method of collecting and counting CA, HO, and CD to infer abnormal traffic conditions.

2.3.2 Mobile Positioning Algorithm

The following are the major location methods currently defined in the Location Service (LCS) specification by the 3rd Generation Partnership Project (3GPP) (3GPP, 2007):

(1) *Assisted GPS* (A-GPS): The A-GPS navigation system is more efficient than traditional GPS positioning as it obtains almanac data from an assisted position server through network connections. This feature saves time by reducing the search for satellites and allowing faster location determination. Typically, A-GPS only requires thirty seconds to position.

(2) *Mobile scan report* (MSR)-based location methods: These methods use the MSR message (e.g., received signal strength indication (RSSI), round-trip delay (RTD), and relative delay (RD)) from the MS to the Base Station (BS) (Chen et al., 2012a; Lin et al., 2011b). The location models can be classified into angle of arrival (AoA), time of arrival (ToA), and time difference of arrival (TDoA). However, this approach requires more computation power to be efficient.

For higher location accuracy, a FPA is proposed to analyze the received signal strength (RSS) by using measure reports and generating the location information of the MS (Kuo & Tseng, 2008; Bshara et al., 2010; Lin et al., 2011b; Chen et al., 2012a; Chen et al., 2013b). This approach involves two stages: calibration and usage. In the calibration stage, the RSS and the geographic location of the MS are collected as training data and stored in a database. The usage stage retrieves the RSS of the MS and uses its algorithm to determine the location of the MS according to the training data in the database. Although the FPA provides higher accuracy in location determination and speed estimation (Lin et al., 2011b), the speed-reporting rate has not been investigated for the feasibility evaluation of the CFVD. This study uses the FPA to estimate the speed of the MS and proposes a model to analyze the speed-reporting rate.

(3) Database lookup methods: MS location is determined through a static database query. When the network receives a location request, it identifies the cell ID of the BS serving the MS and looks up the geographic location of that BS in a database. However, in general, the cell length is about 2 kilometers, and the location error depends on the cell length.

2.3.3 Speed Estimation from Handover Events

Presently, some research efforts focus on using HO events to estimate real-time traffic information. For example, ITIS has developed a complete traffic information system using the Cellular Floating Vehicle Data (CFVD) (Bar-Gera, 2007; Logghe & Maerivoet, 2007). Gundlegård et al. demonstrated good accuracy in handover location for both GSM and UMTS, with the location accuracy being better in UMTS than in GSM (Gundlegard & Karlsson, 2009). Thiessenhusen et al. measured vehicle speed using the double handover (DHO) event and compared the average speeds from cell phone probe data, floating car data, and loop detector data (Thiessenhusen et al., 2003; Ygnace, 2001; Wu et al., 2016). The DHO event can reflect the vehicle speed on a specific roadway to generate an estimation.