Using Intelligent Cooperative System for Travel Flow Management in Autonomous Vehicle Networks

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***Abstract* - This paper describes the use of the intelligent cooperative system for autonomous vehicle network to manage the ravel flow in the urban roads. The intelligent cooperative system aims to reduce the amount of traffic congestion in road networks, and their negative effects, such as delays, waiting time, driver stress, air and noise pollution, and the blocking of emergency vehicles. The proposed algorithm is very successful for two reasons. The intelligent cooperative system in autonomous vehicle network uses performance analysis based on statistical measurement error to improve the accuracy of the forecast model, and the ability to communicate with others vehicles to update its local information based on quality of experience (QoE). The term QoE is defined and relates to how end users perceive the quality of an application or service. QoE is a new element that can play an important role in improving road traffic congestion, especially under abnormal conditions. The data collection to assess driver satisfaction was based on a questionnaire given to drivers, on road traffic management, and on channel demand data in base stations.**

Keywords - cooperative system, travel flow, QoE

I. INRODUCTION

Urban traffic congestion has been a global issue. Over the last two decades, the demand for developing a traffic prediction methodology robust and accurate enough to handle the urban roads, increased rapidly. In many fields like tourism industry that has been growing very rapidly in the last time, human rescue and safety, the need for an accurate forecasting model is necessary. Various forecast schemes [7][16] have been proposed to manage the travel flow information. Meanwhile the robustness and accuracy of the exponential smoothing forecast is high and impressive [2][10]. To reduce the amount of traffic congestion in road networks, and their negative effects, such as delays, waiting time, driver stress, air and noise pollution, and the blocking of emergency vehicles, we have introduced a road traffic data management approach to variations in traffic flow speed in real-time. This new form of management is based on real time (RT) vehicle tracking. When the number of vehicles increases in road networks, high dynamics in traffic flow and increases in travel time follow and traffic management becomes more complex [4], so we have investigated a novel approach that integrates travel observations made by different sources and hybrid applications. Many ITS applications require real-time vehicle positioning data [6]. The main task for a map-matching (MM) algorithm is to identify the correct road segment [8][12]. A navigation system that provides such positioning data consists of three components: a positioning system, such as global positioning system (GPS)[14][16]; a geographic information system (GIS), based road map, and a map-matching (MM) algorithm [8]. In other hand, many autonomous vehicles are equipped with components that will classify them as intelligent vehicles. Such components include sensors and actuators with intra-vehicle communication, and electronic control units for processing and operation control. Vehicles will be equipped with a wireless communication module for supporting three types of communication: vehicle-to-vehicle (V2V) communication; between vehicles and infrastructure (V2I); between vehicles and any neighboring object (V2X) [3]. Cooperative communication aims to use QoE in the ITS to decrease urban road congestion. It is not easy to evaluate QoE; however, to evaluate it in the ITS, we used monitoring methods for urban road traffic based on a forecasting model, base station data, and driver satisfaction data. Driver perception is usually captured by a mean opinion score (MOS) which is expressed on a five point scale, where excellent = 5, good =4, fair =3, poor=2, and bad=1. The minimum threshold for acceptable quality corresponds to a MOS of 3.5.

The rest of the paper is organized as follows: Section 2 presents methodology; section 3 and section 4 show the implementation of the exponential moving average scheme, and conclude the paper.

II. METHODOLOGY

A. Data Collection and Analysis

There are two ways for the travel data collections; the first is the traditional strategy that is based on the sensors and cameras, the second is the modern strategy that is based on the cellular systems. In the last time (second half of 20th century) the phenomenon of traffic congestion has become predominant due to the rapid increase in the number of vehicles. Traffic congestion appears when too many

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vehicles attempt to use a common transportation infrastructure with limited capacity. To reduce the traffic congestion several methods have been proposed. General, the traffic information collected based on sensors or cellular systems. Conceptually, traffic information [1] may fall into one of the three categories as follows; Historical information, real-time information, and Predictive information. The historical data is a collection of past observations of the system. Historical data describe the traffic states of a transportation system during previous time periods. It is mainly used to classify daily graphs or special events. Real-time information is most up-to-date and can be calculated, e.g., by on-line simulations. Predictive information, like traffic forecasts, can help to change the travel behavior of road users by providing information about the future state of the network.

B. Travel Flow Managements

We distinguish between three main kinds of moving average. Simple moving average (SMA), weighted moving average (WMA) and exponential moving average (EMA). A simple moving average is the unweighted mean of the previous data points in the time series. A weighted moving average is a weighted mean of the previous data points in the time series. A weighted moving average is more responsive to recent movements than a simple moving average. An exponentially weighted moving average (EMA) is an exponentially weighted mean of previous data points, the parameter 1 of an EMA can be expressed as a proportional percentage.

$$EMA^F(t) = \alpha * tt(t) + (1-\alpha) * EMA(t-1) \quad (1)$$

The EMA forecast models based on the historical information that we have used till now presented an impressive forecast performance compared to the actual information.

C. Autonomous Vehicle Position

Nowadays, navigation systems such as the GNSS and GPSs are used widely for vehicle position detection [7][9][15] Navigation systems also provide travel information, destination directions, road maps, real-time road conditions, and vehicle speeds. Management of a heterogeneous road network requires locating vehicles within the network [11]. To improve the detection of vehicle positions, a map- matching (MM) method has been proposed. Map- matching is often used to obtain the real-time positions of vehicles in a road network. It aims to identify the correct road segment and to determine the vehicle location on that segment [13]. Various approaches have been proposed. Quddus et al. [13] introduced a map-matching strategy based on distance and orientation, which does not involve any further knowledge about the movement besides the position samples. Civilis et al.in [5] introduced a map-matching algorithm based on edge distance and direction, like that of Quddus, for updating location by tracking the users of location-based services. Yin and Wolfson in [17] proposed an algorithm based on a weighted graph representation of the road network in which the weights of each edge represent the distance from the edge to the trajectory. The improved map-matching method proposed here uses an algorithm based on local path searching and enables better determination of vehicle position within a road network. There are three main form of geometric matching.

III. Performance Analysis

A. Road Traffic Management- Based QoE

In this section, we consider QoE in the management of urban road congestion. The term QoE relates to how end users perceive the quality of an application or service. In this phase we aim to improve resource allocation under abnormal conditions based on mobile host behaviors. QoE monitoring includes monitoring urban road traffic, channel demand in base station, and drivers' experiences.

B. Measurement of Driver Satisfaction

To measure car drivers' (MCD) satisfaction with travel, we need to collect information. The most commonly used survey methods for data collections are focus groups, field surveys, in-vehicle surveys, driving simulators, and video surveys. This section introduces various approaches to collecting data to measure driver satisfaction based on questionnaires, road traffic management, and channel demand in base stations. These are shown in Figure 1.

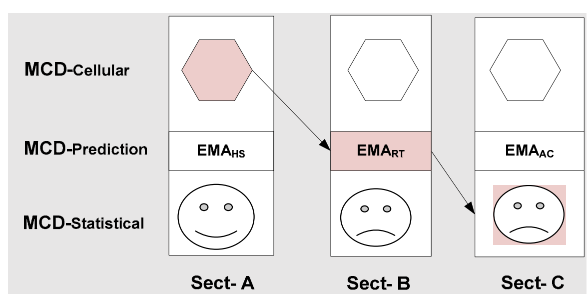

Figure 1: Drivers' satisfaction measurement methods

C. MCD Satisfaction Based Prediction

Various short-term traffic forecasting schemes have been proposed [5][7]. In this section, we introduce a forecasting model based on the moving average. There are three types of moving average: the simple moving average

(SMA), the weighted moving average (WMA), and the exponential moving average (EMA). In this study, an exponential moving average was used. This form of average uses a weighting or a smoothing factor that decreases exponentially. Exponentially decreasing weighting for each older data point, gives much more importance to recent observations, while not discarding the older observations entirely. The forecasting model is divided into two phases: a detection phase, and a forecasting phase. The detection phase focuses on an analyzing collected data. To increase accuracy in this phase we have to detect abnormal events in the data. The forecasting phase is based on the exponential moving average. The robustness and accuracy of the exponential smoothing forecast are impressive. The accuracy of this technique depends on the weight smoothed alpha factor value of the current demand. To determine the optimal alpha factor value, we used a fitting curve. *There are two kinds of exponential moving average (EMA) forecasting: one uses EMA based historical information (HI); the other uses EMA based real-time information (RI) as illustrated in Figure 6.* The historical database is a collection of past travel observations of the system. The exponential smoothing forecasting method distributes weight to the observed time series unequally. This is accomplished by using one or more smoothing parameters, which determine how much weight is given to each observation. The major advantage of the exponential smoothing method is that it gives good forecasts for a wide variety of applications. In addition, the data storage and computing requirements are minimal, which makes exponential smoothing suitable for real-time forecasting.

$$tt(t+1,k) = \alpha * tt^{M}(t,k) + (1-\alpha) * tt^{H}(t,k) \quad (1)$$

where $0 < \alpha \leq 1$, $tt^{M}(t, k)$ is the actual travel time in section *k* at time *t*, and $tt^{H}(t, k)$ is the historical travel time in section *k* at time *t*.

D. MCD Satisfaction Based Cellular System

The cellular concept involves a mobile network architecture composed ideally of hexagonal cells. The cells represent geographic areas. Inside the coverage area, the users, called *mobile stations* (MS) are able to communicate with the network while moving inside the cellular network. Each cell has a *base station* (BS), which serves the mobile stations. Base stations are linked to *a mobile switching centre* (MSC) also called *mobile telephone switching office* (MTSO), which is responsible for controlling the calls and acting as a gateway to other networks. The BS allocates network resources for the users within its cell for communication to take place. When the road congestion increases in a zone, the demand for resources from the base station (BS) increases.

E. MCD Satisfaction Based Questionnaire

To measure driver satisfaction, some methodologies call for a traditional survey questionnaire design. The construction of questions that accurately measure the degree of satisfaction is the most important part of this questionnaire design. All of the questions should be easy to understand. Numerous factors can influence drivers' evaluations of the quality of service, such as the type of vehicle, the number of years a driver has had a license, road quality, and weather conditions. The degree to which each factor in the survey might affect the rating of satisfaction should be considered.

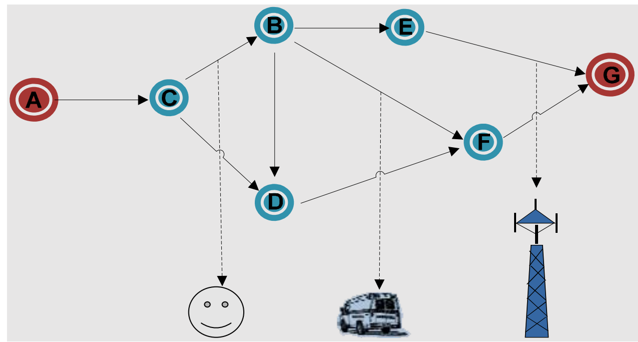

Figure 2: MCD measurements

In a cellular network, each cell is assigned a number of channels. Under a heavy traffic load, if a vacant channel is not found, the call is blocked. Figure 3 illustrates the channel demand in the base stations under accident condition. In some cells, the channel demand is high, which causes call blocking. Figure 3a presents graphs of the road congestion in each section within a city. However, Figure 3b illustrates the road congestion on highways. Table 1 compares the forecasting scheme's historical data (hist) with real-time data (RT) under accident conditions.

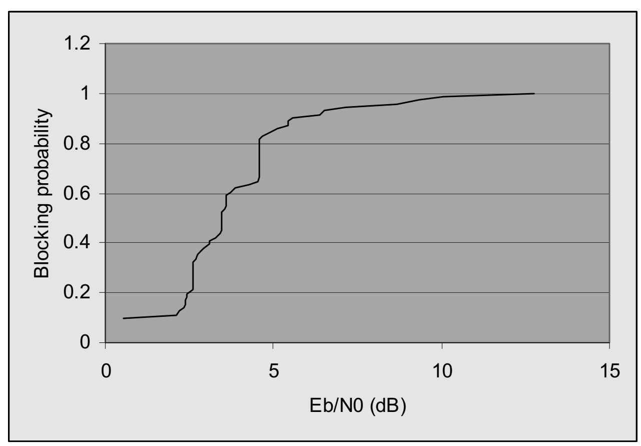

Figure 3: Blocking probability

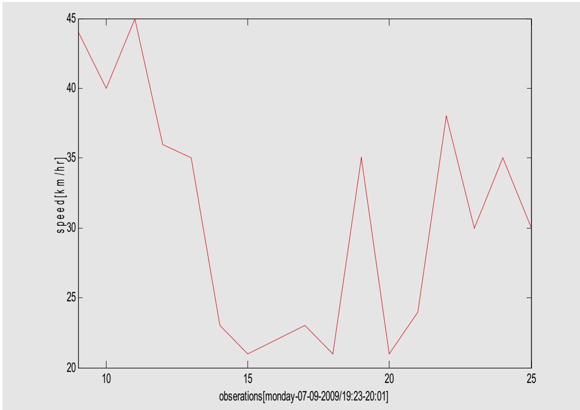

Figure 3a: Urban road congestion

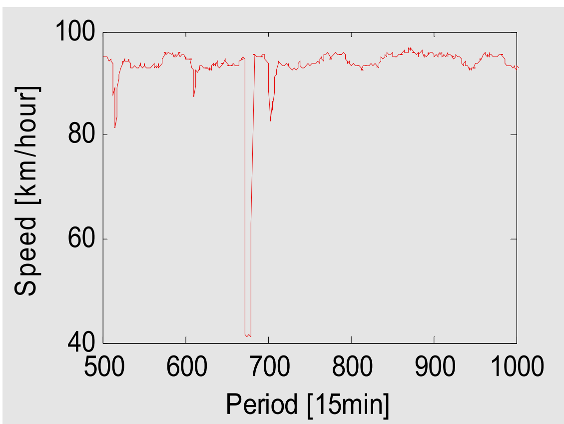

Figure 3b: Urban road congestion

TABLE 1: HISTORICAL DATA COMPARED WITH REAL-TIME DATA

	Hist	RT
mean data	79.234	67.805
mean prediction	75.324	66.798
std data	17.737	17.809
std prediction	22.993	16.968
Observations with error over 5 km/hr	42.206	31.293
Observations with error over 10 km/hr	26.006	15.735
max abs. error	93.492	73.264
max. relative error	1181.7	586.11
mean error	3.9104	1.0076
mean abs. error	10.588	5.472
mean relative error	16.743	10.562
root mean squared error	20.505	9.2418
root mean squared percent error (1)	39.798	23.514
root mean squared percent error (2)	25.88	13.63
Theil's coefficient	12.82	6.6476
bias proportion	3.6367	1.1886
variance proportion	6.57	0.82716
co-variance proportion	89.793	97.984

TABLE 2: SMA VS. WMA VS. EMA

Statistical Measurements	SMA	WMA	EMA
Mean absolute error	6.22	8.11	5.17
Root mean squared error	12.33	14.04	9.57
Relative absolute error	11.84	16.54	11.54
Theil's Coffient	7.21	9.55	5.61

IV. CONCLUSION

In this paper, we have discussed road travel data management based on real time vehicle tracking. The travel data were collected by mobile services. Due to a lack of urban coverage in cellular systems and in the GNSS, we have introduced a cooperative system to increase the accuracy of the forecast model. The new proposed scheme combined two techniques; forecast model and QoE.

QoE was in corporate into an ITS to reduce urban road congestion. To measure the QoE of drivers, various QoE techniques were used, such as a forecasting model, traffic management via base stations and a questionnaire. We believe that the management of QoE requirements with QoS parameters can be helpful to operators and users for maximizing urban road capacity by reducing road congestion.

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REFERENCES

[1] R. Chrobok, O. Kaumann, J. Wahle and M. Scheckenberg,"Three Categories of Traffic Data: Historical, Current, and Predictive", 9th IFAC Symposium, Braunschweig, Germany, 13-15, Vol. 1, June. pp. 221-226.

[2] J. Raiyn, "Speed Adaptation in Urban Road Network Management", Transport and Telecommunication, 17, 2. 2016. pp.11-121

[3] I. Jawhar, N. Mohamed, and H. Usmani, "An Overview of Inter-Vehicular Communication Systems, Protocols and Middleware". Journal of Networks, 8, 12. 2013. pp.2749–2761.

[4] J.L. Adler, G. Satapathy, V. Manikonda, B. Bowles, and V.J.A. Blue, "A multi-agent approach to cooperative traffic management and route guidance". Transport. Res. Part B: Methodology. 39(4), 2005. pp. 297–318.

[5] Civilis, C.S. Jensen, J. Nenortaite and S. Pakalnis, Efficient tracking of moving objects with precision guarantees. In Proc MobiQuitous conf., 2004. pp. 164–173.

[6] W.K. Hong, E. Choi, S. Lee, and M. Heo. "Analysis of GNSS Performance Index Using Feature Points of Sky-View Image". IEEE Transactions on Intelligent Transport Systems. April; 15(2), 2014. pp. 889-895.

[7] J. Gong, Z. Yu, and N. Chen, "An analysis of drivers' route choice behavior in urban road networks based on GPS data". In: Proc. of the Int. Conf. on Transportation Engineering ICTE, American Society of Civil Engineers, July 22-24; 2007, China; 515–520.

[8] 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 15, 2007, pp. 312–328.

[9] J. Raiyn, "Handoff self-management based on SNR in mobile communication networks", Int. J. Wireless and Mobile Computing, 6(1), 2013. pp. 39-48.

[10] J. Raiyn, and T. Toledo, " Real-Time Road Traffic Anomaly Detection", Journal of Transportation Technologies, 4(3), 2014. pp. 1-10.

[11] Ronen, A. Coman, E. Schragenheim, „Peak Management". International Journal of Production Research.; 39, 2001. pp. 3183-3193.

[12] H. Yin, and O.A. Wolfson, "Weight-based map matching method in moving objects databases". In Proc. 16th SSDBM conf., 2004. 437–438.

[13] N.R. Velaga, M.A. Quddus, and A.L. Bristow, "Detecting and Correcting Map Matching Error in Location-Based Intelligent Transport Systems", 12th WCTR, 2010 July, Lisbon, Portugal.

[14] P. Zandbergen, "Accuracy of iPhone Locations: A Comparison of Assisted GPS, WiFi and Cellular Positioning", Transactions in GIS, 13(1), 2009. pp. 5-16.

[15] X. Zheng, and M. Liu, "An overview of accident forecasting methodologies", Journal of Loss Prevention in the Process Industries, 22:, 2009. pp. 484-491.

[16] K. Ramm, and V. Schwieger, "Mobile positioning for traffic state acquisition". J. Location Serv. 1(2), 2007. pp. 133–144.

[17] O. Wolfson, and H. Yin, Accuracy and Resource Consumption in Tracking and Location Prediction, Advances in Spatial and Temporal Databases, 2013. pp 325-343.