A New Context-Aware Approach to Traffic Congestion Estimation

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***Abstract*—Vehicular traffic estimation is one of the major issues in intelligent transportation systems. Traffic information can be used by navigation systems to improve travel efficiency. Current traffic estimation systems rely on infrastructure deployment to monitor traffic state. Therefore, they are costly to implement. In this paper, we propose a new context-aware approach to traffic congestion estimation. The proposed system estimates traffic state based on fuzzy logic without need of any communication infrastructure. The fuzzy system uses vehicular contextual information including speed and acceleration of vehicle to estimate the local traffic congestion level. The proposed system is evaluated using three simulation scenarios with different traffic congestions. Simulation results indicate that the proposed system provides an accurate and efficient estimation of road traffic state, which can be exploited by traffic-aware applications.**

Keywords- Intelligent transportation system; Traffic congestion estimation; Context-awareness; Fuzzy system

I. INTRODUCTION

With the rapid increase of vehicles, road traffic congestion has become a serious problem because a lot of time gets wasted in the congested streets every day. Therefore, traffic state estimation is one of important issues in intelligent transportation systems, which plays a key role in decreasing travel time, improving traffic efficiency, controlling traffic lights, etc.

Traffic state is usually estimated by relying on infrastructure deployment. One of the most common approaches to collect traffic data such as speed, traffic flow, and density is to deploy fixed sensors such as loop detectors [1][2], video cameras [3][4], etc in certain locations of road. The weaknesses of these mechanisms include incomprehensive spatial coverage, low accuracy (because of spotted data collection), and high costs of deployment and maintenance [5]. Some pieces of research make use of probe vehicles as mobile sensors, which periodically transmit their position and speed to a centralized server in order to estimate the traffic state [6-8]. However, these techniques rely on a centralized server for processing and collecting traffic data, which involves considerable computational complexity, single point of failure, and high delays [9].

In recent years, vehicular communication has been exploited for traffic data collection. These approaches do not require the deployment of any infrastructure. In these approaches, vehicles broadcast beacon messages containing information about their position and speed periodically to other vehicles. Vehicles use these beacon messages to measure traffic parameters such as density and speed. Fukumoto et al. [10] propose COC (Contents Oriented Communications) system wherein a vehicle uses beacon messages from other vehicles to estimate traffic density and then transmits this information to nearby vehicles. Other vehicles use the traffic density information to estimate the congestion of different roads. Bauza et al. [11] propose CoTEC (COoperative Traffic congestion detECtion) which builds on a fuzzy logic mechanism to locally estimate road traffic congestion using traffic density and vehicle speed as input parameters. In this system, traffic density is estimated locally by each vehicle using the received beacon messages from other vehicles.

In light of the significant advances in information technology, the new technology of context-aware computing has emerged as an efficient approach to improve the area of transportation performance. Context-aware computing has been used in different areas of transportation including road safety, traffic management, and comfort of drivers. In the domain of context-aware computing, people can use personal services at any time and any place.

Context is the fundamental concept in context-aware computing paradigm. According to Dey, context is defined as "any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves" [12][13]. He defines context-aware systems as "A system that uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task" [12][13].

Context-aware applications of the transportation system use the driving context information such as information related to the driver, the vehicle state, traffic regulations, etc and provide appropriate operations for the vehicle according to the environment situation. This paper makes use of this key technology as a potential for estimating traffic state.

In this paper, vehicles act as traffic sensors and estimate the traffic state locally. Our proposed system does not require any network infrastructure for collecting and processing data, which decreases the expenses effectively. We propose a new context-aware traffic estimation system, which makes use of fuzzy logic to estimate traffic state.

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The proposed system, which is installed on the vehicle, continually measures the contextual information of vehicle including average speed and mean absolute acceleration on a road segment during a specific time period. Afterward, it estimates the local traffic congestion level based on this contextual information. The average speed and mean absolute acceleration of vehicle on a road segment are measured using instantaneous speed sampling by GPS at constant intervals of, for example, 1 to 10 seconds.

In order to evaluate the proposed system, we simulate three scenarios with different congestion levels in a highway environment. We evaluate the system's performance by choosing 10 sample vehicles in each scenario where the average speed and mean absolute acceleration of the vehicles are measured, and the traffic congestion level is estimated using these contextual information based on the proposed fuzzy system. Simulation results indicate that the proposed approach provides an accurate estimation of the traffic state in the different traffic flow scenarios.

The rest of the paper is organized as follows: Section II presents the proposed approach to traffic estimation based on fuzzy logic. Section III presents simulation scenarios to evaluate the proposed approach. Finally, Section IV describes conclusions and future research directions.

II. Proposed Approach

In our proposed approach, vehicles act as mobile traffic sensors that can measure their local traffic state. The proposed context-aware system uses the contextual information including average speed and mean absolute acceleration of the vehicle in order to accurately estimate the traffic state. Each vehicle equipped with the proposed system estimates the traffic congestion level locally, based on a fuzzy logic system. The fuzzy system utilizes average speed and mean absolute acceleration of the vehicle as input parameters and measures traffic congestion level as output parameter. Below, we will first discuss how traffic information is collected and will continue to describe the fuzzy logic based system of traffic congestion estimation.

A. Traffic Information Collection

In general, whenever a vehicle moves at a speed close to the free traffic flow speed, it can be concluded that the road is free of congestion. On the other hand, when the vehicle moves at a low speed, it is inferred that the road traffic is congested. Vehicles' speed can reflect the traffic state and be used as a traffic parameter to evaluate road traffic.

The proposed fuzzy system uses the vehicle's average speed context information as the first parameter. A vehicle's average speed is the mean value of its measured instantaneous speeds. The average speed of a vehicle during a time period T is shown by $\overline{V}_T$ and calculated by the following formula:

$$\overline{V}_T = \frac{v_1 + v_2 + \ldots + v_m}{m} \quad (1)$$

,Where m is the number of speed measurement samples in the specified time interval.

In a free flow state or low congested traffic, a vehicle travels at a relatively uniform speed. In this state, the vehicle's acceleration changes would be a negligible positive or negative value. However in a congested traffic state, the vehicle's speed continually increases or decreases, and its acceleration would be higher positive or negative values. In fact, traffic congestion increases the absolute value of acceleration. Thus, a vehicle's acceleration value can be used as a traffic parameter to evaluate road traffic state. Therefore, we use vehicle's mean absolute acceleration (MAA) as the second parameter. MAA is the mean of the absolute value of vehicle's measured accelerations during a certain time period. The mean absolute acceleration of vehicle during the time period T is calculated by the following formula:

$$MAA_T = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{\Delta v_i}{\Delta t_i}\right| \quad (2)$$

A vehicle's instantaneous speed sampling is conducted at constant intervals in order to measure the mean absolute acceleration. Δv_i is the value of speed changes between speed sampling at the time i and speed sampling at the time i+1, Δt_i is the constant interval of speed sampling between time i and time i+1, and n is the number of samplings during the certain time period e.g. every 5 seconds in a 1 minute time period.

In the proposed approach, each vehicle equipped with the traffic estimation system, records its instantaneous speed by GPS at constant intervals. Therefore, a vehicle collects a profile of its instantaneous speeds during a certain time period. Vehicle's average speed during a certain time period is computed by calculating the mean of recorded instantaneous speed values. Mean absolute acceleration of the vehicle is computed by calculating the mean of measured absolute accelerations during the time period. Then the vehicle estimates local traffic congestion using its average speed and mean absolute acceleration based on a fuzzy logic.

B. Fuzzy Traffic Estimation System

Contextual information measured by a vehicle, which includes average speed and mean absolute acceleration, are applied as input variables to the fuzzy system. The fuzzy system aims to measure the traffic congestion level as the output variable. For this, the Mamdani fuzzy inference system [16] is used, which consists of four major parts: Fuzzification, Fuzzy rule base, Inference engine and Defuzzification.

Fuzzification: In the fuzzification step, the crisp input values are transformed to fuzzy sets (low, medium, high, etc.) using the fuzzy membership functions. The output of this step is the membership grades of input variables regarding the fuzzy sets.

The proposed fuzzy system defines three fuzzy sets of slow, medium, and fast for the vehicle's speed parameter and fuzzy sets of low, medium, and high for vehicle's acceleration parameter. The membership functions used for speed and acceleration variables are shown in Fig. 1. The membership functions and their ranges are tuned manually.

To describe the traffic state, we define four fuzzy sets: free flow, low congestion, medium congestion, and high congestion. Membership functions of traffic state fuzzy sets are also shown in Fig. 1. In the free flow state, the traffic density is very low, and vehicles can move freely at the maximum speed limit. In the high congestion state, the traffic density is high, forcing the vehicles to move very slowly – a situation called traffic jam.

Fuzzy Rule Base: This part contains a number of fuzzy IF-THEN rules. The rule base of the proposed fuzzy system is defined as follows:

1. If (Speed is Slow) and (Acceleration is Low) then (Traffic is Medium)
2. If (Speed is Slow) and (Acceleration is Medium) then (Traffic is Medium)
3. If (Speed is Slow) and (Acceleration is High) then (Traffic is High)
4. If (Speed is Medium) and (Acceleration is Low) then (Traffic is Low)
5. If (Speed is Medium) and (Acceleration is Medium) then (Traffic is Low)
6. If (Speed is Medium) and (Acceleration is High) then (Traffic is Medium)
7. If (Speed is Fast) and (Acceleration is Low) then (Traffic is Free)
8. If (Speed is Fast) and (Acceleration is Medium) then (Traffic is Free)
9. If (Speed is Fast) and (Acceleration is High) then (Traffic is Low)

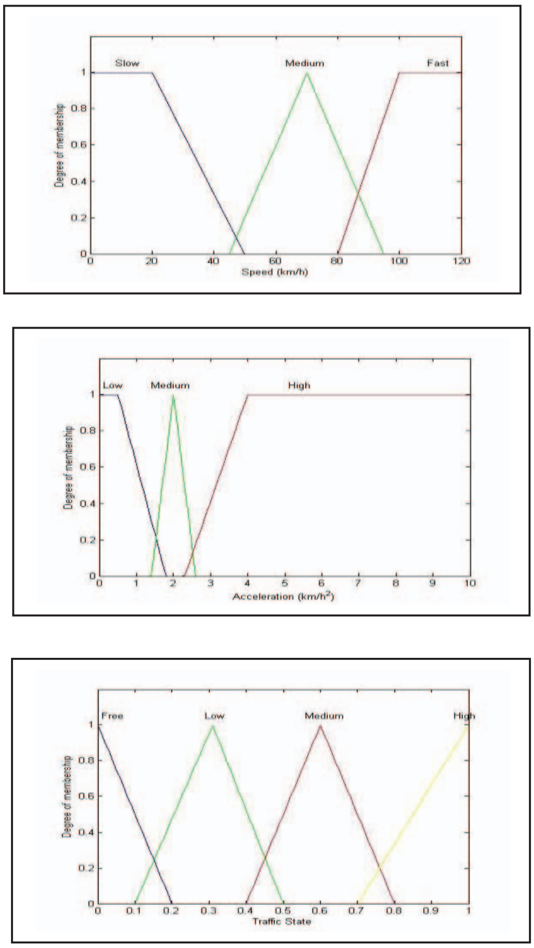

Figure 1. The membership functions used for input and output variables

Inference Engine: The inference engine evaluates all fuzzy rules and determines their output degrees. Then, the aggregation of the rules output is performed to compute the output fuzzy set. Max-Min [17] aggregation is used in this system.

Defuzzification: Defuzzification transforms the output fuzzy set obtained from the inference engine to a crisp value. We use the centre of gravity (COG) [16] method for defuzzification, which finds the geometrical center of the output variable.

The traffic congestion level is measured by each vehicle individually using membership functions of local speed and acceleration parameters and the presented fuzzy rules. The output of the fuzzy traffic estimation system is a value in the range [0,1], which shows the traffic congestion level. The bigger the degree of traffic, the more the road traffic congestion.

III. Performance Evaluation

We use the open source simulator SUMO [18] in order to simulate road traffic. This paper evaluates proposed fuzzy system in a highway environment. For this, a two-lane highway with a length of 2000 m and a maximum speed limit of 120km/h is considered. The flow rate is 1800 vehicles per hour; that is, every 2 seconds, a vehicle enters the highway. The vehicles are distributed uniformly across the highway. We make different traffic congestion levels by decreasing the speed limit on the highway. In this simulation, the vehicles are supposed to be able to travel at the maximum speed limit. Three simulation scenarios are defined with different traffic congestions:

- **Scenario A:** In this scenario, the maximum speed limit on the highway is set to 120km/h. The vehicles travel in a free flow state. In this situation, there is sparse traffic congestion and vehicles can travel freely at a high speed.
- **Scenario B:** In this scenario, the speed limit on the highway is 70km/h. There is low traffic congestion in which vehicles travel at a lower speed.
- **Scenario C:** This scenario simulates a high congestion state, i.e., traffic jam, on the highway. This traffic state is made by setting the speed limit to 20km/h. In this situation, vehicles travel at a very low speed.

In the simulated scenarios, every vehicle records its instantaneous speed at 1 second constant intervals. Then, the vehicle computes its average speed and mean absolute acceleration using the recorded instantaneous speeds of the last 5 seconds period. The vehicle calculates its local traffic state on the basis of this context information. In each scenario, 10 sample vehicles are randomly chosen to validate the proposed traffic estimation system. Sample vehicles' average speed and mean absolute acceleration values are extracted during a certain time period of the simulation. Traffic congestion level is measured using the membership functions of speed and acceleration and the fuzzy rules of the proposed system. We present the simulation results below.

Tables I, II, and III show average speed, mean absolute acceleration, and congestion level values measured by the vehicles in scenarios A, B, and C, respectively. The congestion level values shown in the 4th column of the tables represent the traffic state measured by the proposed fuzzy system.

TABLE I. LEVEL OF TRAFFIC CONGESTION MEASURED BY SAMPLE VEHICLES UNDER SCENARIO A

Vehicles	Average Speed (km/h)	Mean Absolute Acceleration (km/h^2)	Level of congestion
V0	116.44	1.20	0.077
V1	115.32	2.03	0.064
V2	115.55	1.02	0.072
V3	117.31	1.25	0.078
V4	115.34	1.94	0.064
V5	116.47	1.82	0.069
V6	118.16	2.25	0.072
V7	114.34	2.26	0.073
V8	116.68	1.78	0.070
V9	117.12	1.35	0.081

TABLE II. LEVEL OF TRAFFIC CONGESTION MEASURED BY SAMPLE VEHICLES UNDER SCENARIO B

Vehicles	Average Speed (km/h)	Mean Absolute Acceleration (km/h^2)	Level of congestion
V0	66.91	1.50	0.301
V1	68.06	0.88	0.303
V2	66.13	1.76	0.303
V3	67.26	1.87	0.303
V4	67.81	2.33	0.315
V5	67.73	1.84	0.303
V6	65.28	2.40	0.350
V7	66.59	2.09	0.303
V8	66.10	0.62	0.303
V9	68.09	2.10	0.303

TABLE III. LEVEL OF TRAFFIC CONGESTION MEASURED BY SAMPLE VEHICLES UNDER SCENARIO C

Vehicles	Average Speed (km/h)	Mean Absolute Acceleration (km/h^2)	Level of congestion
V0	15.13	4.72	0.903
V1	15.21	2.75	0.872
V2	16.91	3.26	0.889
V3	15.80	3.20	0.887
V4	15.20	5.35	0.903
V5	15.72	3.10	0.884
V6	16.61	3.20	0.888
V7	14.54	3.59	0.898
V8	14.17	2.62	0.866
V9	16.11	4.12	0.903

The accuracy of the proposed system is evaluated by two metrics, the mean and standard deviation. Table IV shows mean and standard deviation of traffic congestion level measured by the sample vehicles in simulated scenarios.

By observing traffic fuzzy sets, it can be concluded that scenario A with the mean congestion level of 0.072 shows free flow state. Besides, scenario B with the mean congestion level of 0.3087 and scenario C with the mean congestion level of 0.8893 simulate low congestion state and traffic jam, respectively. In addition, the low values of standard deviation in simulated scenarios mean that the proposed approach has low dispersion to estimate traffic state, which indicates high accuracy of the this fuzzy system.

TABLE IV. MEAN AND STANDARD DEVIATION OF LEVELS OF TRAFFIC CONGESTION MEASURED IN THREE SCENARIOS

	Scenario A	Scenario B	Scenario C
Mean	0.072	0.3087	0.8893
Standard deviation	0.005617	0.015026	0.012979

IV. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a new context-aware approach based on fuzzy logic that uses contextual information including speed and acceleration of a vehicle to measure local traffic congestion. The proposed fuzzy system utilizes the vehicle's average speed and mean absolute acceleration as input variables, and measures traffic congestion level as output. The vehicle's average speed and mean acceleration have been computed by vehicle's instantaneous speed sampling. Our proposed system has estimated the local traffic state of vehicles in an efficient way and without need of any network infrastructure.

To validate the proposed system, we have evaluated it using three scenarios with different congestions of free flow, low congestion, and traffic jam. The experiment results indicate that simultaneous use of vehicle's speed and acceleration could estimate acceptable and accurate congestion level in different traffic states.

In continue, we will evaluate the performance of the proposed system by more complicated simulation scenarios and environments such as urban road network. The recent advances in vehicular communication systems have provided vehicle-to-vehicle communications and information exchange between vehicles. Another direction for future research is to extend the proposed approach through mechanism of sharing traffic information between vehicles in order to estimate global roads traffic level.

REFERENCES

[1] B. Coifman, "Improved velocity estimation using single loop detectors," Transportation Research Part A: Policy and Practice, vol. 35, no. 10, pp. 863-880, December 2001.

[2] B. Coifman, S. Dhoorjaty, and Z.-H. Lee, "Estimating median velocity instead of mean velocity at single loop detectors," Transportation Research Part C: Emerging Technologies, vol. 11, no. 3/4, pp. 211-222, June–August 2003.

[3] Y. Cho, and J. Rice, "Estimating velocity fields on a freeway from low-resolution videos," IEEE Transactions on Intelligent Transportation Systems, vol. 7, no. 4, pp. 463-469, December 2006.

[4] B. T. Morris, and M. M. Trivedi, "Learning, modeling, and classification of vehicle track patterns from live video," IEEE Transactions on Intelligent Transportation Systems, vol. 9, no. 3, pp. 425-437, September 2008.

[5] W. L. Leow, D. Ni, and H. Pishro-Nik, "A sampling theorem approach to traffic sensor optimization," IEEE Transactions on Intelligent Transportation Systems, vol. 9, no. 2, pp. 369-374, June 2008.

[6] B. R. Hellinga, and L. Fu, “Reducing bias in probe-based arterial link travel time estimates,” Transportation Research Part C: Emerging Technologies, vol. 10, no. 4, pp. 257-273, August 2002.

[7] Y. Li, and M. McDonald, “Link travel time estimation using single GPS equipped probe vehicle, ” Proceedings 5th International IEEE Conference on Intelligent Transportation Systems, pp. 932-937, September 2002.

[8] Y. Zhu, Z. Li, H. Zhu, M. Li, and Q. Zhang, “A compressive sensing approach to urban traffic estimation with probe vehicles,”IEEE Transactions on Mobile Computing, vol. 12, no. 11, pp. 2289-2302, November 2013.

[9] L. Garelli, C. Casetti, C. Chiasserini, and M. Fiore, “Mobsampling: V2V communications for traffic density estimation,” IEEE 73rd Vehicular Technology Conference (VTC Spring), pp. 1-5, May 2011.

[10] J. Fukumoto, N. Sirokane, Y. Ishikawa, T. Wada, K. Ohtsuki, and H. Okada, “Analytic method for real-time traffic problems by using Contents Oriented Communications in VANET, ” 7th International Conference on ITS Telecommunications, pp. 1-6, June 2007.

[11] R. Bauza, and J. Gozálvez, “Traffic congestion detection in large-scale scenarios using vehicle-to-vehicle communications,” Journal of Network and Computer Applications, vol. 36, no. 5, pp. 1295-1307, September 2013.

[12] A. K. Dey, “Understanding and using context,” Personal and ubiquitous computing, Springer-Verlag London, vol. 5, no. 1, pp. 4-7, February 2001.

[13] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles, “Towards a better understanding of context and context-awareness, ” in Handheld and ubiquitous computing, H.-W. Gellersen, Eds. Springer Berlin Heidelberg, 1999, pp. 304-307.

[14] M. Baldauf, S. Dustdar, and F. Rosenberg, “A survey on context-aware systems,” International Journal of Ad Hoc and Ubiquitous Computing, Inderscience Publishers, vol. 2, no. 4, pp. 263-277, June 2007.

[15] S. Fuchs, S. Rass, B. Lamprecht, and K. Kyamakya, “Context-awareness and collaborative driving for intelligent vehicles and smart roads, ” 1st International Workshop on ITS for an Ubiquitous ROADS, pp. 1-6, 2007.

[16] J. H. Lilly, “Mamdani Fuzzy Systems, ” in Fuzzy Control and Identification, John Wiley & Sons, 2010, pp. 27-45.

[17] I. Baturone, A. Barriga, C. Jimenez-Fernandez, D. R. Lopez, and S. Sanchez-Solano, Microelectronic design of fuzzy logic-based systems, illustrated ed. CRC press, 2000.

[18] D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker, “Recent development and applications of SUMO–simulation of urban mobility,” International Journal On Advances in Systems and Measurements, vol. 5, no. 3 and 4, pp. 128-138, December 2012.