Journal of Ergonomics

Li et al., J Ergonomics 2016, 6:1
DOI: 10.4172/2165-7556.1000144

Short Communication Open Access

Fuzzy Lane-Changing Models with Socio-Demographics and Vehicle-to-Infrastructure System Based on a Simulator Test

Qing Li*, Fengxiang Qiao and Lei Yu

Innovative Transportation Research Institute, Texas Southern University, Houston, TX 77004, USA

***Corresponding author**: **Qing Li,** Innovative Transportation Research Institute, Texas Southern University, Houston, TX 77004, USA, Tel: 713-313-1915; E-mail: **Qiao_FG@TSU.EDU**

Received date: November 12, 2015; **Accepted date: December** 9, 2015; **Published date:** December 19, 2015

Abstract

Objective: We investigated the impacts of drivers' socio-demographic factors on these lane-changing models, and developed Fuzzy logic-based lane-changing models associated the drivers' demographic factors.

Methods: Forty drivers were recruited for a driving simulator test to collect their driving behaviors of changing lane in a work zone with/without the aid of Driver's Smart Advisory System (DSAS), a Vehicle-to-Infrastructure (V2I) communication system. Fuzzy table look-up scheme was selected to model Lane-Changing Reaction Time (LCRT) and Lane-Changing Reaction Distance (LCRD) incorporated with drivers' socio-demographic information and the collected driving behaviors.

Findings: Without DSAS messages, the elders slowly responded to a static traffic guide of lane-change, but they didn't change lane at the last minute. The highly educated and young drivers changed lane the earliest. When DSAS messages were provided, all drivers' LCRT became shorter while their LCRD longer.

Conclusion: Drivers' age and the level of education are essential socio-demographic factors in lane-changing process. The DSAS is able to instruct all drivers to take earlier lane-changing actions. The developed models can predict drivers' LCRT and LCRD accurately.

Key words:

Lane-changing model; Fuzzy logic model; Drivers' socio-demographic factors; V2I technology; Drivers' Smart Advisory System (DSAS)

Introduction

A Lane-changing model is one of the fundamental components functioning in a microscopic traffic simulation that can assess traffic performance on highway and street systems, in transit, and among pedestrians [1]. Therefore, traffic simulation and modeling have been widely employed in transportation engineering and planning practices [2]. To gain more realistic drivers' driving behaviors and assess more accurately traffic performance, many efforts have been made in formulating lane-changing models [3-9], which are normally designed for static traffic control signs, such as stop and speed limit signs. In recent years, the development of Intelligent Transportation System (ITS) has promoted the application of Vehicle-to-Infrastructure (V2I) wireless communication technology to improve drivers' awareness on dynamic traffic situations [10-14]. However, the change in driving behaviors affected by the V2I system has not yet been taken into account in the existing lane-changing models. Further, the effects of a V2I system are very sensitive to drivers' socio-demographic factors, which have been confirmed by [15] and [11]. With regard to this, this research was proposed to develop two Fuzzy logic-based lane-changing models, including the Lane-Changing Reaction Time (LCRT) model and the Lane-Changing Reaction Distance (LCRD) model. Drivers' socio-demographic factors were considered in the design of models for a mandatory lane-change in a work zone equipped with a Drivers' Smart Advisory System (DSAS).

Subjects and Methods

A driving simulator test was conducted to collect drivers' natural driving behaviors during lane-change process, the data set of which was used to develop a fuzzy logic based LCRT and LCRD models. The developed models were applied to different cities with various socio-demographic specifications. The LCRT is the measured duration to complete a lane-changing action, while the LCRD is referred to the distance between the point that a driver started to change lane, and the point that the vehicle's heading turns right back to 90o in the target lane.

Forty subjects were recruited based on the Houston 2010 census demographic distribution. They were above 18 years old with a valid C class USA driver's license. Five of them had less than three years driving experience, while 35 subjects had longer than 3 years. All subjects have self-reported that they had normal or corrected-to-normal vision and hearing. Subjects were requested to drive twice through a standardized work zone for rural area with the speed limit of 48 km/h (30 mph), without and with DSAS messages. Vehicles' geo-location, heading degree, speed, and lane index were collected at a frequency of 10 Hz.

Seventy-five percent (30 subjects) of dataset was used for modeling. Based on all available input-out data pairs, a fuzzy rule-base was created and an IF-THEN rule based fuzzy table look-up scheme was employed to calibrate models for LCRT and LCRD, respectively. The

Citation: Li Q, Qiao F, Yu L (2016) Fuzzy Lane-Changing Models with Socio-Demographics and Vehicle-to-Infrastructure System Based on a Simulator Test. J Ergonomics 6: 144. doi:10.4172/2165-7556.1000144

fuzzy system used is with the product inference engine, singleton fuzzifier, and center average defuzzifier, which is expressed in Equation (1) [16].

$$f(x) = \frac{\sum_{l=1}^{M} \bar{y}^{l}\left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i)\right)}{\sum_{l=1}^{M}\left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i)\right)} \rightarrow (1)$$

where, f(x) is LCRT or LCRD, the output of the fuzzy system; is the center value of fuzzy set in the THEN part for the l^{th}lth rule; $\mu_{A_i^l}(x_i)$ is the membership function of the rule for the l^{th} component of the input vector x_i; M is the total number of fuzzy rules. There are four input variables in this research: gender (x_1) , age (x_2), education background (x_3), and driving experience (x_4).The Membership Functions (MF) were defined using the popular triangle functions for and , and singleton functions for x_1 and x_3. There are two fuzzy sets for x_1 (F as female, and M as Male); three fuzzy sets for (Y as young for age 0 to 25; M as medium age for age 26 to 65; and O as old for age 65+); two fuzzy sets for (H as high school degree, and B as Bachelor or higher degree), and two fuzzy sets for x_4 (N as non-experience, and E as experience).

For the output, the MF for LCRT and LCRD also used the triangle functions with seven sets for each, ranging from 0-45s and 0-152m, respectively.

The developed models were applied to estimate drivers' LCRT and LCRD in five different cities. Their specific socio-demographic specifications are shown in Table 1.

Feature	City	Specification
Female city	Roseland, IN	77.2% female population
Male city/Low Education	Madeline Plains, CA	64.2% male population, 86.5% High school or below
Old city	Punta Gorda City, Fl	51.6% elders (65+)
Young city/High Education	West University Place, TX	80.4% medium (26-65); 79.4% Bachelor or higher
Low Education	Stockton City, CA	82.5% High school or lower

Table 1: Socio-demographic information for simulation illustration.

Results and Discussion

Without the aid of DSAS, the discrepancy in LCRT and LCRD was irregular among the five cities and the national average. Old drivers responded to a static guide of lane-change slowly, but they did not change lane at the last minute. The highly educated and young drivers changed lane the earliest. When DSAS messages were provided, all drivers' LCRT and LCRD became shorter and longer, respectively. Besides, the developed models performed acceptable errors ranged from 1.82% to 2.42% for LCRT and from 0.38% to 3.06% for LCRD.

To validate the accuracy of the developed LCRT and LCRD models, the estimated values from models were compared with the recorded values from simulator tests. Results show the error rates were less than 10%. The error rates of models ranged from 0.38% to 2.42%, with standard deviations from 3.75% to 7.20%. Such tiny errors demonstrate that the developed models can accurately estimate drivers' LCRT and LCRD. The developed models were applied to five cities with specific socio-demographic features. The model-estimated LCRT and LCRD are shown in Table 2.

City's Socio-demographic features		Proportion (%)	LCRT (s)			LCRD (m)		
			Without DSAS	With DSAS	Difference	Without DSAS	With DSAS	Difference
Gender	Female city	F: 77.2; M: 22.8	30.80	24.19	6.61	428.00	325.05	102.95
	USA average	F: 50.9; M: 49.1	31.72	21.64	10.08	441.35	304.50	136.85
	Male city	F: 35.8; M: 64.2	32.76	22.61	10.15	449.90	336.00	113.90
Age	Old city	Mi: 43.0; O: 51.6	34.39*	22.83	11.56	448.25	310.35	137.90
	USA average	Mi: 65.6; O: 16.1	31.72	21.64	10.08	441.35	304.50	136.85
	Young city	Mi: 80.4; O: 10.2	31.24	17.45*	13.79	460.15*	252.40*	207.75
Education	Lowly	H: 82.5; B: 17.5	31.57	23.30	8.27	428.50	324.90*	103.60
	USA	H: 63.2; B: 36.8	31.72	21.64	10.08	441.35	304.50	136.85

	Highly	H: 20.6; B: 79.4	31.24	17.45*	13.79	460.15	252.40*	207.75
Note: F=Female; M=Man; Mi=Middle age between 25 and 64; O=Old age 65+; H= High School or lower; B= Bachelor or higher; *significantly different from others.								

Table 2: Simulated LCRT and LCRD with different socio-demographic specifications.

In Table 2, the LCRTs and LCRDs are generally shorter in the scenario with DSAS messages than the ones without the messages across all socio-demographic factors. This implies that the DSAS messages are able to assist all drivers to take an earlier lane-changing action and efficiently complete the action.

In the scenario with traditional traffic control signs only (without DSAS), drivers' LCRTs and LCRDs performed irregularly among different cities and the national average. It was hard to find a common pattern for different socio-demographic specifications. It is striking that the LCRT in old city is visibly longer by 2.67 s to 3.15 s (elders=34.39 s; USA=31.72 s; Young=31.24 s), but they didn't change lane at the last minute (LCRD=448.25 m). The longer LCRT can be explained by 'slowing effect' [11,17]. Meanwhile, the relatively long LCRD indicates that the elders paid more attentions to static objects such as the pavement parkers, which is consistent with the finding by Dukic and Broberg [18] and Botwinick [19].

Besides, the LCRDs in the young city and the city with higher education level were relatively longer (460.15 m) than in the old city (448.25 m), the city with lower education level (428.50 m), and the national level (441.35 m). Compared with the elders, it is convinced that the youngsters normally take a necessary action quicker when the traffic situation is allowed. Moreover, the highly educated drivers are more likely to follow the traffic control signs [11].

When the DSAS message was provided, the differences mentioned became weaker and even improved. The LCRT for elders decreased from 34.39 s to 22.83 s, which is similar to national level (21.64 s). The LCRDs declined from 460.15 m to 252.4 m for the young city, and from 460.15 m to 252.40 m for the city with high education level, which were even shorter than the national level of 304.50 m. This indicates that the DSAS messages could help drivers to make a decisive lane-changing action. The decisive lane-changing action may be due to drivers' confidence in changing lane at a right moment. Besides, the LCRTs in young city (17.45 s) and the city with high education level (17.45 s) were relatively lower than the one in national level (21.64 s), the old city (22.83 s), and the lowly educated city (23.30 s), in the scenario with the DSAS. It was more likely that young and highly educated drivers were able to adapt to the DSAS quickly and performed better in lane-changing process.

Conclusion

Based on the dataset collected from a simulator test, a fuzzy based LCRT and LCRD models were developed, which accurately predict and estimate drivers' lane-changing response time and distance. The application of the developed models in five cities with different socio-demographic distributions shows that, drivers' age and the level of education are determinative factors for their lane-changing performance. The introduction of DSAS is able to weaken the impacts of the factors and even improve drivers' lane-changing action.

Acknowledgment

The authors acknowledge that this research is supported in part by the Tier 1 University Transportation Center TranLIVE #DTRT12GUTC17/KLK900-SB-003, and the National Science Foundation (NSF) under grants #1137732. Please refer to the paper [20] for more detailed information on this research.

References

1. FHWA (2004) Traffic Analysis Toolbox, Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software. U.S. Federal Highway Administration, Mclean.
2. Ranjitkar P, Nakatsuji T, Kawamua, A (2005) Car-following models: an experiment based benchmarking. Journal of the Eastern Asia Society for Transportation Studies 6: 1582-1596.
3. Chandler RE, Herman R, Montroll EW (1958) Traffic dynamics: studies in car following. Operations Research 6: 165-184.
4. Liu RH, Vliet DV, Watling DP (2006) Microsimulation models incorporating both demand and supply dynamics. Transportation Research Part A: Policy and Practice 40: 125-150.
5. Rorbech J (1976) Multilane traffic flow process: evaluation of queuing and lane-changing patterns. Transportation Research Record 596: 22-29.
6. Ahmed KI, Ben-Akiva ME, Koutsopoulos HN, Mishalani R G (1996) Models of freeway lane changing and gap acceptance behavior. In: Proceedings of the 13th International Symposium on Transportation and Traffic Theory, Lyon.
7. Ahmed KI (1999) Modeling Drivers' Acceleration and Lane Changing Behavior. Massachusetts Institute of Technology, Cambridge.
8. Kita H (1993) Effects of merging lane length on the merging behavior at expressway on-ramps. In: Proceedings of the 12th International Symposium on the Theory of Traffic Flow and Transportation, Berkeley.
9. Yang Q, Koutsopoulos HN (1996) A microscopic traffic simulator for evaluation of dynamic traffic management systems. Transportation Research Part C: Emerging Technologies 4: 13-129.
10. Lin PS, Beaubien R, Lower JA (2013) Connected vehicles and autonomous vehicles: where do ITE members stand? ITE Journal 83: 31-34.
11. Li Q, Qiao FX (2014) How Drivers' Smart Advisory System Improves Driving Performance? : A Simulator Imitation of Wireless Warning on Traffic Signal under Sun Glare. LAP LAMBERT Academic Publishing.
12. Qiao F, J Jia, L Yu, Q Li, D Zhai (2014) Drivers' Smart Assistance System Based on Radio Frequency Identification. In Transportation Research Record: Journal of Transportation Research Board, No. 2458, Transportation Research Board of the National Academies, USA 37-46.
13. Li Q, F Qiao, L. Yu (2015) Will Vehicle and Roadside Communications Reduce Emitted Air Pollution? International Journal of Science and Technology 5: 17-23.
14. Li Q, F Qiao, X Wang, L Yu (2015) Driving Performance Test of Stop Signs with Drivers Smart Advisory System. Publication in the proceedings of the 28th Annual Conference of the International Chinese Transportation Professionals Association, USA.
15. Nauert R (2011) Aggressive Drivers Identify with Their Car. Retrieved from the Psychcentral.
16. Wang LX (1997) A Course in Fuzzy Systems and Control. Upper Saddle River, NJ: Prentice Hall PTR.

17. Underwood G, Grundall D, Chapman P (2011) Driving simulator validation with hazard perception. Transportation Research Part F 14: 435-446.
18. Dukic T, Broberg T (2012) Older drivers' visual search behavior at intersections. Transportation Research Part F: Traffic Psychology and Behaviour 15: 462-470.
19. Botwinick J (1966) Cautiousness in advanced age. Journal of Gerontology 21: 347-353.
20. Li Q, F Qiao, L Yu (2015) Socio-demographic impacts on lane-changing response time and distance in work zone with drivers' smart advisory system, Journal of Traffic and Transportation Engineering 2: 5.