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Lane Change Guidance System

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Abstract: A lane changing assistance system. It advises drivers of safe gaps for making mandatory lane changes. It refers the parameters such as vehicle's position, speed, velocity, acceleration, de-acceleration etc. These parameters are present into the vehicles trajectory dataset. The freeway lane selection algorithm helps to take appropriate decision for a lane change.

Bayes classifier and decision-tree methods were applied to model lane changes. Two main classifiers that are used for assisting the system are Bayes classifier and decision tree. The best results were obtained when both Bayes and decision-tree classifiers are used. The prediction accuracy was 94.3% for non-merge events and 79.3% for mergeevents. Thus by using the freeway lane selection algorithm we can improve the accuracy of nonmerge eventsup to some larger extent.

Index terms: *Vehicle trajectory dataset, Freeway lane selection algorithm, Bayes classifier, decision tree.*

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I. INTRODUCTION

Increasing traffic density has becoming a severe problem day by day. Thus lane change becomes challenging task .While changing a lane, driver has to think about many factors about the traffic environment. In case any wrong decision occurs it may result in an accident.Limited research exists on other forms of lane changing assistance systems. In this paper, a lane changing assistance system that advises drivers of safe and unsafe gaps for making mandatory lane changes is developed.

Lane changing models describe drivers' lane changing behaviors under various traffic conditions. These models are an essential component of microscopic traffic simulation and have been extensively studied in the literature. Many of the literature on lane changing models is based on gap acceptance.

A driver makes a lane change when both the lead and lag gaps in the target lane are acceptable. [3]Distribution of critical lead and lag gap lengths, various gap acceptance models were built in 1960s and 1970s. Herman and Weiss assumed an exponential distribution for critical gaps, Drew et al. assumed lognormal distribution, and Miller assumed a normal distribution. Daganzo modeled driver's merging from the minor leg of a stop-controlled T-intersection to the major leg using a probit model. Kita modeled driver's merging behavior from freeway on-ramp using a logit model for gap acceptance. Yang and Koutsopoulos invented a rule-based lane changing model that was incorporated into the microscopic simulator MITSIM.Ahmed et al. developed a generic lane changing model that captures lane changing behavior under mandatory and discretionary lane changes. Kita also developed a game-theoretic lane changing model[7]. A two-person non zero non cooperative game was developed to model the interaction of drivers in the target lane and the merging lane. Hidas used intelligent-agent-based techniques to model driver's lane changing behavior and implemented the model in the ARTEMiS traffic simulator [18].

In summary, several types of lane changing models have been proposed in the literature with the main goal of developing accurate traffic simulation models. However, none of these models were intended for use in a real-time lane changing assistance system that advises drivers of when it is safe or unsafe to merge.

One main difference between the simulation and the lane change assistance system applications is the relative importance of misclassification between merge and nonmerge decisions[9]. In a simulation model, the effect of a nonmerge event misclassified as a merge event only affects the mobility measures. The same misclassification, however, in a lane change assistance system could impact traffic safety significantly. Thus, any model of lane change targeted for use in vehicles as part of an assistance system must give more importance to not misclassifying nonmerge events as merge events. On the other hand, misclassifying a merge event as a nonmerge event would result in a lost opportunity to merge but would not have a negative safety effect. Many of the models proposed in the literature are not appropriate for this new application.

Bayes classifier and decision-tree methods[4] are applied to develop models for mandatory lane changes at lane drops. Both methods have been applied extensively in machine learning systems built for decision-making in many disciplines. They have several advantages for modeling lane changing. Both of them relax the assumptions of traditional lane changing model's mathematical forms and variable distributions. Therefore, they can mimic the complex nonlinear nature of driver's lane changing behavior more realistically. One additional advantage of a Bayes classifier is its ability to take into account the cost of misclassification. Bayes classifier, it is possible to assign a higher cost of misclassification to non-merge events than to merge events. Bayes classifier and decision-tree models were developed using the same training and validation data.[2] Then, both classifiers were integrated into a single hybrid classifier. The combined classifier, when tested on a new data set from a different highway segment, outperformed the individual classifiers in terms of the accuracy of nonmerge events. Mandatory lane changes at lane drops refer only to those executed by traffic entering from a ramp.

II. Materials &Methodologies

Lane change detection and tracking for safe lane change based on in real time vision based navigation system.

It's a lane change assistance system, which is going to assist the driver for making an appropriate lane change**.** The safety of driving cars could be significantly increased by using driver assistance systems[10]
Which interpret traffic situations autonomously and support the driver. An important componentof a driver assistance system is the evaluation of image sequences recorded with camerasmounted in a moving vehicle. Image sequences provide information about the vehicle'senvironment which has to be analyzed in order to really support the driver in actual trafficsituations. It consist of camera which is mounted on the vehicle for the evaluation of the images.Images provide information vehicle environment which has to be analyzed in order to support the driver in actual situation.it is based on computer vision helpful in relieving contradictionsbetween enhancement of traffic safety and increment of traffic density. It detects a dangerous condition. Lane departure detection module is an important part of the system. It controls the lateral position on the road. For lateral control most crucial variables to be sensed are position and orientation of vehicle
Steps of image processing used are Image segmentation, edgedetection, Houghtransform, lane tracking.

Emergency lane assistance:

It includes new automotive safety function called ELA [1]i.e. a lane guidance system with threat assessment module which activates and deactivates lane change interventions according to actual risk level of lane departure. This algorithm makes use of vehicle surrounding information i.e.position, motionof the vehicle but also information about road and lane geometry. Parameters are estimated by using KALAMEN filters

Tracking system: Need knowledge about vehicle surroundingwhich means lane geometry and other vehicles

Dynamic motion model: The co-ordinatinate system is used for location of vehicle on the road, which considers the concepts such as longitude latitude, velocity of the vehicle[11].

Decision algorithm:It is most commonly used algorithm for decisionmaking. It detects the correctness of action. It can also identify the risk factors along with dangerous situation. But it doesn't consider the varying objects.

3.Maneuver lane change assistance system: Lane change is a very demanding maneuver. It supports the driver for lane change from its first intention of making a lane change up to the last action of executing it.It covers lane change timing, direction as well as required acceleration and decelerations.

It makes use of various modules

Sensor diagnosis module:

It checks the hardware and software for its functionality and deliver sensor diagnosis signal.

System state check:

It receives the sensor diagnosis signal and prototype the vehicle velocity and drives the activation request. It outputs the system state signal.

Lane change abortion check:

When a lane change is started a module continuously checks maneuver for safe execution. But suddenly any vehicle decelerates then it can calculate the risk and aborts the decision for lane change.

Lane allocation:

It identifies all possible gaps for lane changing and information is needed about lane allocation of detected vehicles[19].

4. Lane change behavior modelling for autonomous vehicles based on surrounding recognition.

Algorithm proposed in this system determines the vehicle trajectory for autonomous lane changing system. It makes use of vehicle sensing signals like velocity, positions of the vehicles. It calculates lane change timing and references theoretically.

Decision model:

It generates longitudinal & lateral acceleration signals with appropriate lane change timing

It is divided into two steps

1. Understanding the spatial constraints for lane change

2. Selecting optimal lane change approach

These contains are based on Intervehicular distances with preceding vehicle ,safe inter-vehicle distance with rearward vehicle & after reaching a lane marker it should keep a safe distance along with other vehicles. This model provides better longitudinal and lateral acceleration and this algorithm has good consistency with experimental data.

5.Adjacent Lane Detection and Lateral Vehicle Distance Measurement
Using Vision-Based Neuro-Fuzzy Approaches.

Adjacent lane detection:

The lane-line detection is intended to extract the lane markers without previously knowing the internal or external parameters of the mounted camera. When the vehicle navigates in the middle of the lane, the lane boundary on the left side shown in the captured image will tilt to the left invertical direction. Based on this feature, we define a 5x5 tilt mask and apply it on the gray-level image to retrieve the edge pixels in the tilt direction. If the calculated value is greater than *thp*, the color of the edge pixel will be set to green (positive edge). While the value is less than *thn*, the color will be set to red (negative edge). The derived image and the thresholds for positive and negative edges are set to 10 and -10 while illustrations[15,18] .Moreover, if the distance between positive and negative edges, marked with green and red colors, is less than ten, the pixels between them will be colored black. Then, all pixels except black ones in this image are colored white to get the binary image. A region near the host vehicle is prespecified. Within this region, a fan scanning detection method is applied to exclude noise data. This method scans the edge pixels from the bottom to top, and left to right. The first encountered pixel in each row is saved, but all the other pixels at the same row are deleted[14]. They are scanned from bottom to top, and the continuous and adjacent edgepoints of same direction are grouped into line segments. This is done by checking the bottom right and limit-sized area of each encountered edge pixel. If there exists an endpoint of linesegment created previously, the encountered pixel will accede to the found line segment. Otherwise, the encountered pixel will create a new line segment

Distance measurement of lateral vehicle**:** The detection method for neighboring vehicle isbased on the Mei's method [11], but we add and modify some steps to enhance the detectionperformance. In this method, the region of interest (ROI) on the lane is transformed into a rectangular area by lane-based transformation [16-17]. Each connected component in this area will be verified with its features, such as length, width, time duration, and height, to determine whether it is a vehicle[13].

III Conclusion:

In this paper, we study models for mandatory lane changes at lane drops were developed using Bayes classifier and decision-tree methods. And the decision will be made by freeway lane selection algorithm. The algorithm actually based on two criteria such as selecting the target lane and acceptance of gap. [6]It refers vehicle trajectory data set that consists of traffic conditions approaching congestion and congested conditions was used for model development and testing. The model employed factors, such as the vehicle speeds relative to the lead and lag vehicles in the target lane, the lead and lag gap distances, and the distance from the beginning of merge lane[12]. Previous research focused on developing models for use in microscopic simulation, whereas this paper has focused on the design of a lane changing assistance system. One main difference between the simulation and the lane change assistance system applications is the relative importance of misclassification between merge and non merge decisions accuracy rates of 94.3%, 95.4%, and 96.7% for non merge events, and 79.3%, 73.6%, and 49.5% for merge events. The cost of misclassification can be treated as a surrogate to driver conservativeness. The greater the cost, the more conservative or less aggressive a driver is in working toward the gap to change lane. As the cost of misclassification increases, the accuracy for non merge events also increases, but the accuracy for merge events decreases. Thus by making use of the freeway lane selection algorithm ,the accuracy of merge events can be improve up to some larger extent[20].

REFERENCES

[1] Emergency lane change assistance system ELA *Oper. Res.*, vol. 9, no. 6, pp. 828–840, Nov./Dec. 1961.

[2] D. R. Drew, L. R. LaMotte, J. H. Buhr, and J. A. Wattle worth,
"Gap acceptance in the freeway merging process," Texas Transp. Inst.,
College Station, TX, USA, 1967.

[3] A. J. Miller, "Nine estimators of gap acceptance parameters," in *Proc. 5th*
Int. Symp. Theory Traffic Flow Transp., 1972, pp. 215–235.

[4] C. F. Daganzo, "Estimation of gap acceptance parameters within and
Across the population from direct roadside observation," *Transp. Res. B*,vol. 15B, no. 1, pp. 1–15, Feb. 1981.

[5] P. G. Gipps, "A model for the structure of lane changing decisions,"*Transp. Res.*, vol. 20B, no. 5, pp. 403–414, Oct. 1986.

[6] H. Kita, "Effect of merging lane length on the merging behavior at expressway on-ramps," in *Proc. 12th Int. Symp. Theory Traffic Flow Transportation*, 1993, pp. 37–51.

[7] Q. Yang and H. N. Koutsopoulos, "A microscopic traffic simulator for evaluation of dynamic traffic

ISSN: 2321-8169
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management systems," *Transp. Res. C*, vol. 4, no. 3, pp. 113–129, Jun. 1996.

[8] Adjacent Lane Detection and Lateral Vehicle Distance Measurement Using Vision-Based Neuro-Fuzzy Approaches."Models of freeway lane changing and gap acceptance behavior," in *Proc.13th Int. Symp. Transp. Traffic Theory*, 1996, pp. 501–515.

[9] H. Kita, "A merging-giveway interaction model of cars in a merging section: A game theoretic analysis," *Transp. Res. A*, vol. 33, no. 3/4, pp. 305–312, Apr. 1999.

[10] P. Hidas, "Modeling vehicle interactions in microscopic simulation ofmerging and weaving," *Transp. Res. C*, vol. 13, no. 1, pp. 37–62, Feb. 2005.

[11] T. Toledo, H. N. Koutsopoulos, and M. Ben-Akiva, "Integrated driving behavior modeling," *Transp. Res. C*, vol. 15, no. 2, pp. 96–112, Apr. 2007.

[12] Q. Meng and J. Weng, "A classification and regression tree approach for predicting drivers' merging behavior in short-term work zone merging areas," *J. Transp. Eng., ASCE*, vol. 138, no. 8, pp. 1062–1070, Aug. 2012.

[13] Y. Hou, P. Edara, and C. Sun, "A genetic fuzzy system for modelingMandatory lane changing," in *Proc. 15th Int. IEEE Conf. Intell. Transp.Syst.*, 2012, pp. 1044–1048.

[14] [14] Next Generation Simulation Fact Sheet,Washington, DC, USA.[Online].Available: ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm

[15] C. Choudhury, V. Ramanujam, and M. Ben-Akiva, "Modeling acceleration Decisions for freeway merges," *Transp. Res. Rec.*, vol. 2124, pp. 45–57, 2009.

[16] H. Yeo, A. Skabardonis, J. Halkias, J. Colyar, and V. Alexiadis, "Oversaturated Freeway flow algorithm for use in next generation simulation,"*Transp. Res. Rec.*, vol. 2088, pp. 68–79, 2008.

[17] "NGSIM U.S. 101 Data Analysis Summary Report," Federal Highway V. Punzo, M. T. Borzacchiello, and B. Ciuffo, "Estimation of vehicle

[18] Trajectories from observed discrete positions and next-generation simulation Program (NGSIM) data," presented at the Proc. 88th Annu. Meeting Transportation Research Board, Washington, DC, USA, 2009.

[19] A. Kesting and M. Treiber, "Calibrating car-following models using trajectorydata: a methodological study," presented at the Proc. 87th Annu. Meeting Transportation Research Board, Washington, DC, USA, 2008.

[20] A. Duret, C. Buisson, and N. Chiabaut, "Estimating individual speedspacing Relationship and assessing the Newell's car-following model Ability to reproduce trajectories," presented at the Proc. 87th Annu..