Lane changing models: a critical review

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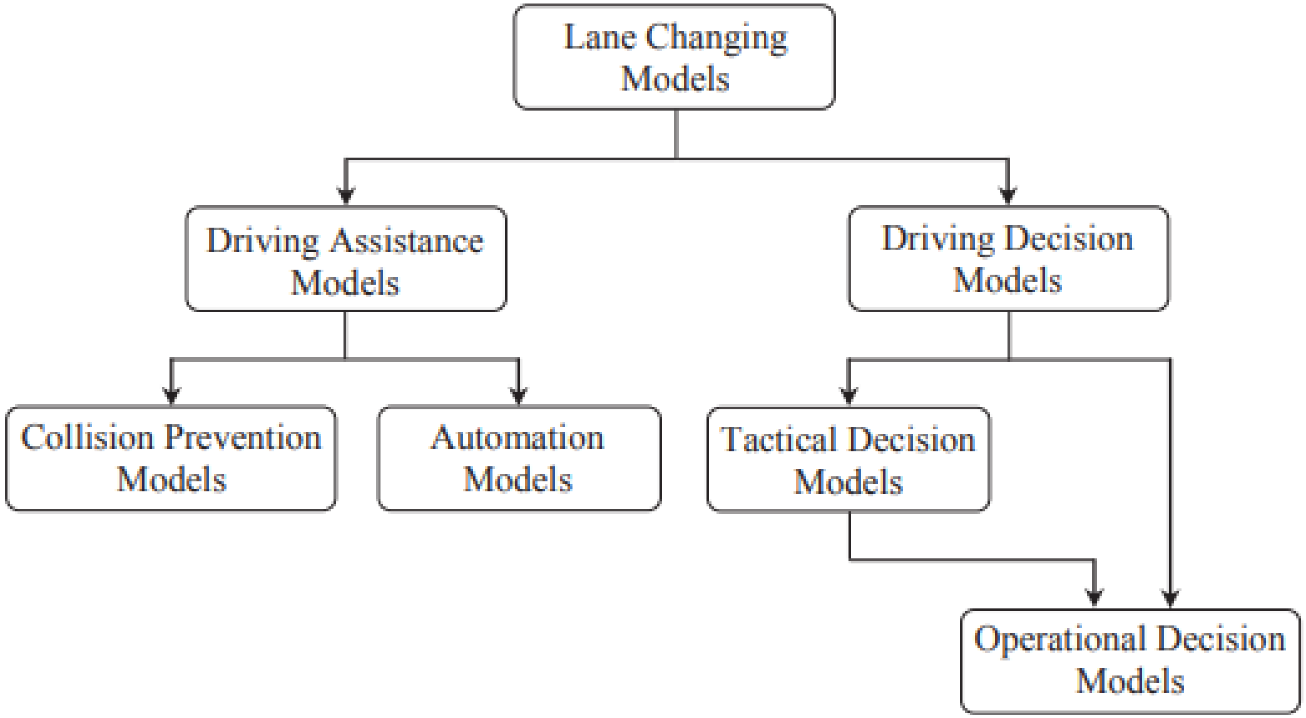
contents

1. Introduction



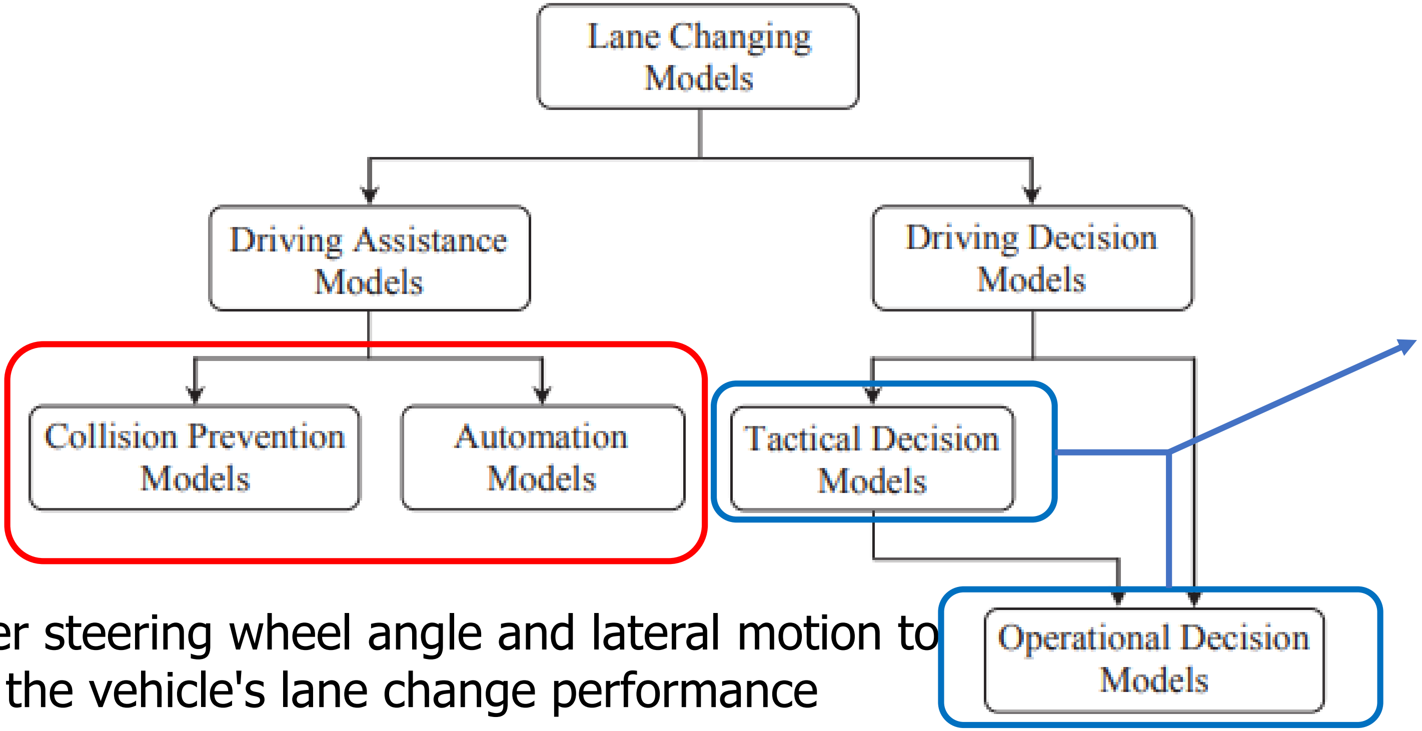
Lane change manoeuvre

- Interference effect on surrounding vehicles
- Fundamental impact on the macro and micro characteristics of traffic flow

The main focus

- Review existing lane change models and evaluate their strengths and weaknesses
- Distinction between the driving assistance model and the driving decision model

2. A classification scheme for lane changing models

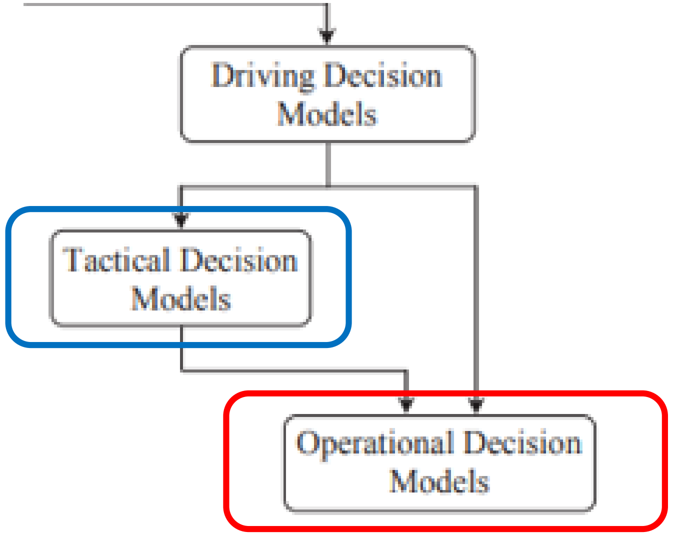


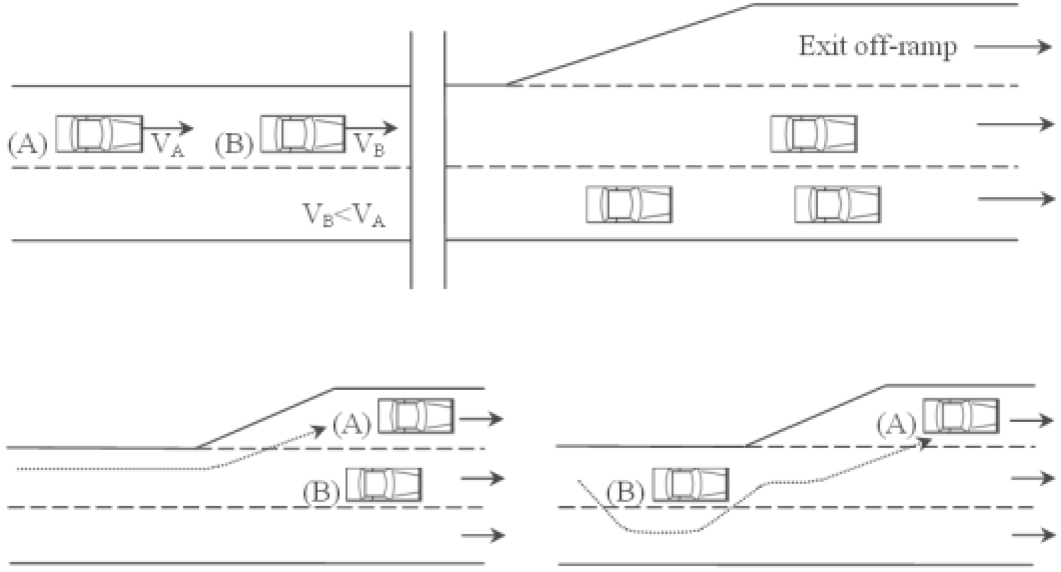
- Driver’s choice of destination
- Traffic mode
- Route is a strategic driving decision

- Consider steering wheel angle and lateral motion to control the vehicle's lane change performance

- Focus on the driver's lane change
- Decision under different traffic conditions
- Different circumstances
- Environmental characteristics

2. A classification scheme for lane changing models





(a) Response 1: Remaining behind the slow moving vehicle and taking the exit off-ramp.

(b) Response 2: Passing the slow moving vehicle and taking the exit off-ramp.

- Covering driver decisions that take more than 30 seconds
- Including the purpose or goal of the trip and the choice of route

- Less than 5 seconds of work
- e.g.) Maneuvering control work for vehicle control

3. Driving decision models

Use an explicit search process to estimate the future position of drivers

- Estimate the location of the vehicle in the near future
- Consequences of the choice the driver faces
- Estimate the driver's decision to change lanes

3. Driving decision models

Look for associations with surrounding traffic characteristics

- Request for the driver's tactical and operational lane change decisions based on the characteristics of the surrounding traffic

3.1 Lane changing decision models based on a search algorithm

Sukthankar / Schlenoff / Webster / Gipps

- The driver's tactical lane change decision is based on a search algorithm
- The driver's operational lane change decision is based on the characteristics of the surrounding traffic
- The search algorithm estimates the driver's lane change decision

⇩

Used to estimate the location of the vehicle in the near future

3.1 Lane changing decision models based on a search algorithm

Sukthankar

- Simulating a driver's decision is similar to designing a responsive robot
- The driver's tactical lane change decision is based on a search algorithm
- The driver's operational lane change decision is based on the characteristics of the surrounding traffic

3.1 Lane changing decision models based on a search algorithm

Schlenoff

PRIDE(PRediction In Dynamic Environment)

- Hierarchical framework for moving object prediction incorporating multiple prediction algorithms into a single framework
  - Input of an algorithm: the current position and speed of the vehicle
  - For future behavior, the algorithm generates the following set of possible locations and allocates a cost to each behavior
  - Assume that the surrounding vehicle does not carry out any lane change manoeuvres
  - Consider interactions between vehicles only as probability of collision between them

3.1 Lane changing decision models based on a search algorithm

Webster(Simulation)

- Development of lane change decision model based on forward search algorithms

- Forward search algorithm generates a branch tree of sequential behavior at each time step for each modeled vehicle

- Forward search algorithm:

- Start at the initial time stage

- Constructed with the speed and position of the subject vehicle and the surrounding vehicle within the field of view specified by the model parameters

3.1 Lane changing decision models based on a search algorithm

Webster(Simulation)

Comparison of simulations of Gipps and Websters

70 simulation vehicles

Means : 0.045 / 0.040

$$U_{LC} = \frac{1}{N}\sum_{i=1}^{N} \delta_i$$

U_{LC} Lane change model performance index

i Number of time steps during the simulation period

$\overline{N}$ Total number of time steps

δ_i If the lane change manoeuvres estimated at time phase i match the observed lane change manoeuvres / otherwise 1

3.1 Lane changing decision models based on a search algorithm

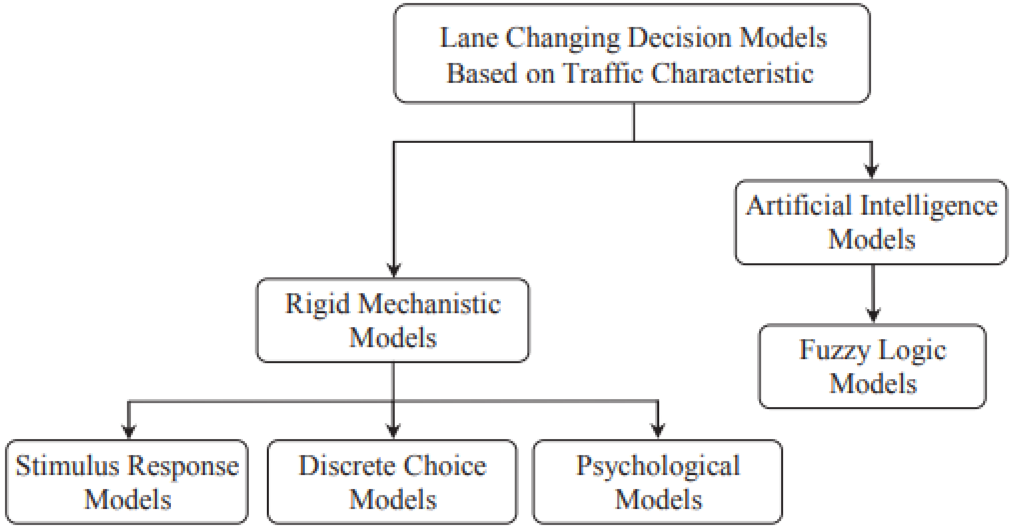
Webster(Simulation)

- Lane change decision models rely on a number of simplified assumptions

1. Assume that the surrounding vehicle does not change acceleration/deceleration or perform any lane change maneuvers

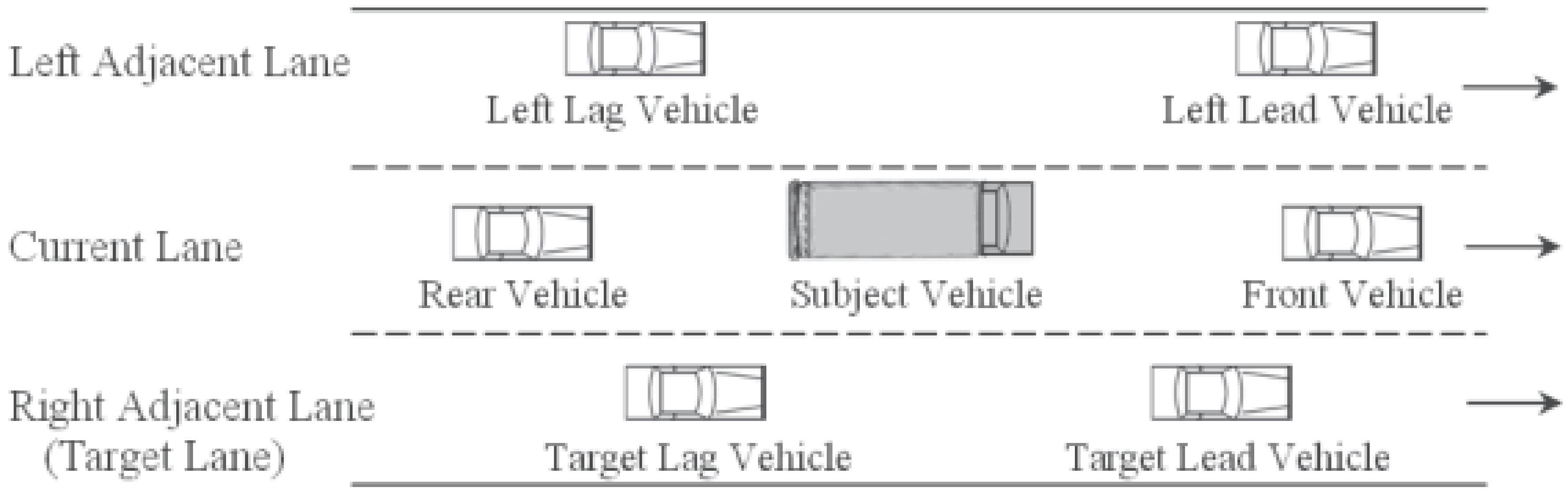
2. Lane change decisions are also limited to situations with acceptable gaps in adjacent lanes

3.2 Lane changing decision models based on traffic characteristics



- The driver's tactical and operational lane change decisions are based on the characteristics of the surrounding traffic

3.2 Lane changing decision models based on traffic characteristics



Parameters

- Subject vehicle
- Location of the surrounding vehicle
- Speed and acceleration / deceleration
- Space clearance / Relative speed of the surrounding vehicle relative to the subject vehicle

3.2.1 Rigid mechanistic models

- Models that create a clear relationship between descriptive and dependent variables

- The magnitude of the result depends on the exact value of the independent variable

- Mechanical lane change approaches generally do not involve uncertainty related to the driver's perceptions and decisions

3.2.1.1 Stimulus response models

Gipps

- Propose a framework for lane change decisions and the structure of lane change execution
- Useful for describing lane change decision on highways / city streets where traffic signals, obstacles and large vehicles influence the driver's decision

- Consider three factors
  - Whether it is physically possible and safe to change lanes
  - Do you need to change lanes
  - Is it desirable to change lanes

3.2.1.1 Stimulus response models

Gipps

Define three zones (Based on the distance to the intended exit point)

- When the exit point is far away / Does not affect the driver's decision to change lanes
- When the exit point is in the middle / Driver ignores lane change opportunities to move away from the desired exit point (Speed Advantage)
- When the exit point is close / Be in the correct lane or adjacent lane

3.2.1.1 Stimulus response models

The Gipps's car following model

- Putting a certain limit on the driver's braking rate
- Maintains a safe speed for the preceding vehicle

The driver's desired speed and safe speed

- Consider at the same time to avoid the effects of slow vehicles or obstacles at a distance

$$v_n(t+T) = b_n T + [b_n^2 T^2 - b_n(2(x_{n-1}(t) - s_{n-1} - x_n(t)) - v_n(t)T - v_{n-1}(t)^2 / b_{n-1}^{est}]^{1/2}$$

3.2.1.1 Stimulus response models

The Gipps's car following model

$$v_n(t+T) = b_n T + [b_n^2 T^2 - b_n(2(x_{n-1}(t) - s_{n-1} - x_n(t)) - v_n(t)T - v_{n-1}(t)^2/b_{n-1}^{est}]^{1/2}$$

$v_n(t+T)$	/	Safety speed of vehicle n relative to the preceding vehicle at time (t + T)
$b_n < 0$	/	Maximum braking rate
T	/	The interval between velocity and position calculations
$x_n(t)$	/	Front position of vehicle n at time t
s_{n-1}	/	Effective length of vehicle n-1
b_{n-1}^{est}	/	Estimates of b_{n-1} used by the driver of n

The maximum safety speed is limited by the driver's desired speed and maximum braking

3.2.1.1 Stimulus response models

The Gipps's car following model

- Never validated using microscopic traffic and driver behavior data
- Application in several microscopic traffic simulations

Based on simplified assumptions

- Lane change occurs when there is a sufficient length of clearance and it is safe to change lanes
- Differences between drivers and within drivers are not taken into acc ount

3.2.1.1 Stimulus response models

Wiedemann / Reiter

Assume that the vehicle is affected by wind

Lane change classification

Slow lane -> Fast lane / Fast lane -> Slow lane

- The desire to move to a fast lane is due to obstruction caused by slow-moving vehicles in the current lane
- Assume that all drivers' decisions are based on human perception
- Categorize surrounding impacts into real and potential impacts

Real impacts : Distance / Relative speeds

Potential impacts : Diriver’s estimation of the surrounding vehicles’ situations in the near future

3.2.1.1 Stimulus response models

Wiedemann / Reiter → Development of a general lane change decision model

- Using macro characteristics of traffic flow to validate lane change decision model
- Estimate lane occupancy for each lane as a function of traffic volume and traffic density
- Compare to the corresponding values in the field dataset
- Provide quantitative indicators for interpreting estimation results X

3.2.1.1 Stimulus response models

Hidas

- Consideration of the following vehicle drivers in the target lane during lane change manoeuvres
- Free lane change: Observe changes in leading and following vehicle intervals X
- Forced lane change: Decrease the interval between the preceding and following vehicles before the start of lane change -> increase after
- Cohesive lane change: the opposite pattern of forced lane change

3.2.1.1 Stimulus response models

Hidas

- A forced lane change algorithm based on the driver's example concept
- Assume that the driver makes a polite request to the driver of the subsequent vehicle in the target lane when executing the lane change maneuver
- Requests are rejected or accepted depending on a number of factors, such as the position, speed, and driver type of the following vehicle
- Good-mannered drivers prepare enough gaps for lane change vehicles --> slow down
- Assume lane change is possible if there is sufficient clearance in the target lane

$$g_l = g_{0l} - (v_s\, b_s /2) + v_l$$
$$g_f = g_{0f} - (v_f\, b_f /2) + (v_s\, b_s /2)$$

3.2.1.1 Stimulus response models

Hidas

$$\boxed{g_l} = \boxed{g_{0l}} - (v_s b_s/2) + v_l$$
$$\boxed{g_f} = \boxed{g_{0f}} - (v_f b_f/2) + (v_s b_s/2)$$

g_l : clearance from the preceding vehicle

g_f : clearance from the following vehicle

g_{0l} : Space gap between the preceding vehicles at the start of lane change

g_{0f} : Space gap between the following vehicles at the start of lane change

v_s : Speed of the subject vehicle

v_l : Speed of the target preceding vehicle

v_f : Speed of the target trailing vehicle

b_s : Deceleration of the subject vehicle

b_f : Deceleration of the following vehicle

This equation allows you to calculate the vehicle spacing

3.2.1.1 Stimulus response models

Hidas

Equation of space with the following vehicle

$$g_f = g_{0f} - (v_f D_t - b_f / 2\, D_t^2) + v_s D_t$$

$$D_t = D_v \;/\; b_f$$

D_v = Reduction of the speed of the subject vehicle

3.2.1.1 Stimulus response models

Hidas

Spatial Equation for the preceding vehicle

$$g_{l,min}=g_{min}+\begin{cases} c_l(v_s-v_l) & \text{if } v_s>v_l \\ 0 & \text{otherwise} \end{cases} \quad g_{f,min}=g_{min}+\begin{cases} c_f(v_f-v_s) & \text{if } v_f>v_s \\ 0 & \text{otherwise} \end{cases}$$

g_{min} = Minimum safe interval independent of speed difference between vehicles = jam gap

$$\left.\begin{matrix} c_l \\ \\ c_f \end{matrix}\right\} \quad \text{A constant number}$$

3.2.1.1 Stimulus response models

Hidas

ARTEMiS (Analysis of Road Traffic and Evaluation by Micro Simulation)

- Test in a simple hypothetical road network scenario
- Reviewing macro-traffic characteristics and their impact on micro-traffic characteristics
- Comparison of velocity-flow curves between HCM method and ARTEMiS model
- ARTEMiS model is close to HCM curve

3.2.1.2 Discrete choice models

Ahmed (Probabilistic model to describe lane changing decisions)

Development of a probability model to describe lane change decisions based on a discrete selection framework

Three successive stages of modeling

1. Decisions to consider lane changes

2. Selection of the destination lane

3. Sufficient space in the target lane to execute the lane change decision

- Mandatory Lane Changing (MLC)
- Discretionary Lane Changing (DLC)
- Forced merge (FM)

3.2.1.2 Discrete choice models

Ahmed (Probabilistic model to describe lane changing decisions)

$$P_t(LC \mid v_n) = \frac{1}{1 + \exp\left(-X_n^{LC}(t)\beta^{LC} - \alpha^{LC} v_n\right)}$$

$$LC = MLC,\ DLC,\ FM$$

$P_t(LC \mid v_n)$	Probability that driver n runs MLC, DLC, Forced Marge (FM) at time t
$X_n^{LC}(t)$	Explanatory variable vector influencing lane change decision
β^{LC}	Vectors of corresponding parameters
v_n	Driver Specific Random Variables
α^{LC}	Parameters for v_n

3.2.1.2 Discrete choice models

Ahmed (Probabilistic model to describe lane changing decisions)

$$G_n^{cr,\,gap\,j}(t) = \exp(X_n^{cr,\,gap\,j}(t)\ \beta^{gap\,j} + \alpha^{gap\,j}\ \nu_n + \varepsilon_n^{gap\,j}\ (t))$$
$$gap\ j = \text{lead, lag}$$

$G_n^{cr,\,gap\,j}(t)$	The gap between the significant preceding and following vehicles with respect to the driver n at time t
$X_n^{cr,\,gap\,j}(t)$	Vectors of explanatory variables that affect critical gaps j
$\beta^{gap\,j}$	Vectors of corresponding parameters
ν_n	Driver specific random term
$\alpha^{gap\,j}$	Parameters in v_n
$\varepsilon_n^{gap\,j}\ (t) \sim N(0,\sigma_{\varepsilon j}^2)$	A random term
$G_n^{lead}\ (t)\ G_n^{lag}\ (\mathrm{t})$	Gap between the preceding and following vehicles available in the target lane

3.2.1.2 Discrete choice models

Ahmed (Probabilistic model to describe lane changing decisions)

Probability of allowing space in MLC, DLC, FM

$$P_n(\,gap\ acceptance|v_n) =$$
$$P_n(lead\ gap\ acceptable|v_n) \times P_n(lag\ gap\ acceptable|v_n) =$$
$$P_n(G_n^{lead}\ (t) > G_n^{cr,\ lead}\ (t)|v_n) \times P_n(G_n^{lag}\ (t) > G_n^{cr,\ lag}\ (t)|v_n)$$

3.2.1.2 Discrete choice models

Toledo

- Lane changing decision model which allows drivers to consider both MLC, DLC at the same time

Using a Discrete Selection Framework
Development of Probabilistic Lane Change Model

Use maximum likelihood estimation → Calibration

Determination of lane change in two stages

Select the destination lane

Clearance Acceptance Decision

Use four group categories

- Peripheral Variables (Peripheral Space, Speed)
- Path Planning Variables
- Network knowledge and experience
- Driving style and driving ability

3.2.1.2 Discrete choice models

Toledo

$$U_n^{lane\ i}(t) = X_n^{lane\ i}(t)\ \beta^{lane\ i} + \alpha^{lane\ i}\nu_n + \varepsilon_n^{lane\ i}(t)$$
$$lane\ i = CL,\ RL,\ LL$$

$CL,\ RL,\ LL$

Current lane / right lane / left lane

$U_n^{lane\ i}(t)$	Utility of lane i to driver n at current lane / right time t && lane / left lane
$X_n^{lane\ i}(t)$	Vectors of explanatory variables that affect the utility of suboptimal i
$\beta^{lane\ i}$	Vectors of the corresponding parameters
$\varepsilon_n^{lane\ i}(t)$	Random term related to suboptimal utility
ν_n	Driver specific random term

3.2.1.2 Discrete choice models

Toledo

Probability of each driver choosing a particular lane: Calculated using the logit model (Equation below)

$$P_n(lane\ i_t \mid v_n) = \frac{exp\ [X_n^{lane\ i}(t)^{lane\ i} + {}^{lane\ i}v_n]}{\sum_{j \in I} exp\ [X_n^{lane\ i}(t)^{lane\ j} + {}^{lane\ h}v_n]}$$

$$lane\ i,\ lane\ j\ I = \{CL,\ RL,\ LL\}$$

3.2.1.2 Discrete choice models

Toledo

$$\ln\left(G_n^{gap\ j,\ TL,\ cr}(t)\right) = X_n^{gap\ j,\ TL}(t)\ \beta^{gap\ j} + \alpha^{gap\ j}\nu_n + \varepsilon_n^{gap\ j}(t)$$
$$gap\ j = lead,\ lag$$

- General form of Toledo's critical niche model
- Assume that the critical gap is always positive
- Assume to follow a log-normal distribution

$G_n^{gap\ j,\ TL,\ cr}(t)$	Important gap g of the target lane measured in meters
$X_n^{gap\ j,\ TL}(t)$	Vectors of explanatory variables that affect significant gap j
$\beta^{gap\ j}$	Vectors of the corresponding parameters
$\varepsilon_n^{gap\ j}(t) \sim \mathrm{N}(0, \sigma^2_{gap\ j})$	A random term
$\alpha^{gap\ j}$	Parameters of driver specific random term v_n
$G_n^{lead,\ TL}(t)$ $G_n^{lag,\ TL}(t)$	Prior and Subsequent Gaps

3.2.1.2 Discrete choice models

The French National Institute for Research in Transportation and Safety

- It is not possible to comment in detail on the structure of the model or to evaluate its performance

- omission

3.2.2. Artificial Intelligence models (AI)

McDonald / Das / Bowles

- Traditional lane change decision
- A clear mathematical equation
- Use traditional logic rules
- Include random terms to capture fluctuations around the mean value

3.2.2. Artificial Intelligence models (AI)

Das

- Fuzzy IF-THEN rules → Autonomous Agent SIMulation Package(AASIM)

Classify lane change manoeuvres into MLCs and DLCs

AASIM's DLC rules reflect binary decisions based on two explanatory variables
(whether lane changes are made)

Specific lane change decision model for each vehicle type is not considered

Driver satisfaction level formula

$$\sigma_t = (1 - \varepsilon) \times \sigma_{t-1} + \varepsilon \times \left(\frac{v}{v_{lim}}\right)$$

3.2.2. Artificial Intelligence models (AI)

Das

Driver satisfaction level formula

$$\sigma_t = (1 - \varepsilon) \times \sigma_{t-1} + \varepsilon \times \left(\frac{v}{v_{lim}}\right)$$

σ	Driver satisfaction
v	Vehicle speed during the current iteration
v_{lim}	The speed limit on the highway
ε	Percentage of Learning Satisfaction

3.2.2. Artificial Intelligence models (AI)

Das

- The level of congestion in the left and right adjacent lanes

$$c = \frac{\sum_{all\ i} e^{-d_i/\Delta} \times \left(1 - \frac{v}{v_{lim}}\right)}{\sum_{all\ i} e^{-d_i/\Delta}}$$

c	Local lane congestion from the driver's point of view
d_i	distance to the i-th vehicle
Δ	Parameters
$(e^{-d_i/\Delta})$	Weight related to the i-th vehicle : exponentially decreasing with distance

3.2.2. Artificial Intelligence models (AI)

Das

- General form of fuzzy rules

$$j^{th} \text{ rule: If } I_1 \text{ is } \boldsymbol{A}_{1j} \text{ and } \ldots I_i \text{ is } \boldsymbol{A}_{ij} \text{ and } I_m \text{ is } \boldsymbol{A}_{mj} \text{ then } O \text{ is } \boldsymbol{B}_j$$

$I = f(I_1, I_1, \ldots, I_n)$	Input Variables
A_{ij}	Fuzzy subset for input I_j
O	Output
B_j	Fuzzy subset for output O

3.2.2. Artificial Intelligence models (AI)

McDonald / Brackstone / Wu

Fuzzy Logic Motorway Simulation Model (FLOWSIM)

Classified into two categories

low lane change : Run so as not to interfere with the fast approaching vehicle from behind

fast lane change : Run to get speed advantage

3.2.2. Artificial Intelligence models (AI)

McDonald / Brackstone / Wu

Fuzzy Logic Motorway Simulation Model (FLOWSIM)

Pressure From Rear	Gap Satisfaction	Intension of Moving into Right Lane
High	Good	High
Medium	Moderate	Medium
Low	Bad	Low

A fuzzy set used to develop a lane change decision model to a slow lane

If pressure from rear is ***Low*** and gap satisfacion is ***High*** then intention of moving into right lane is ***Medium***

3.2.2. Artificial Intelligence models (AI)

Model Types		
Stimulus Response	**Probabilistic**	**Fuzzy Logic**
General Procedure for Model Development		
• Decide on explanatory variables. • Calibrate the models (Gipps 1986; Wiedemann and Reiter 1992).	• Decide on: 1. Independent stages. 2. Explanatory variables. 3. Probability functions. • Calibrate the probabilistic functions (Ahmed 1999; Choudhury et al. 2007; Toledo 2009).	• Decide on: 1. Explanatory variables. 2. Fuzzy sets and membership function. 3. Rule sets. • Calibrate the models (McDonald et al. 1997; Brackstone et al. 1998; Das et al. 1999; Wu et al. 2000; Wu et al. 2003).
Stages in Model Development and Explanatory Variables (EV)		
• Decide on MLC or DLC (Gipps 1986). EV: Maximum subject vehicle's safe speed and brake, front gap, subject vehicle driver's estimation of front vehicle driver's brake. • Decide on lane change to either faster or slower lane (Wiedemann and Reiter 1992). EV: Lane change duration, time and distance headways to surrounding vehicles.	• Decide on changing lanes. EV: MLC-Exit/merge distance, number of lane changes, DLC-Presence of heavy vehicle, front relative speed and deceleration (Ahmed 1999). • Select the target lane. EV: Subject vehicle speed, target lead and lag gaps and relative speeds, presence of heavy vehicle, tailgating, avoiding the right-most-lane, distance to the exit off-ramp (Ahmed 1999; Toledo 2009). • Accept a gap. EV: Target lead and lag relative speeds, distance between target lead and lag (Ahmed 1999; Toledo 2009).	• Decide on MLC or DLC (Das et al. 1999). *MLC or DLC* EV: MLC-Exit/merge distance, number of lane changes, DLC-Left and right lane density, drivers' satisfaction. *Find a gap in target lane.* EV: Front, lead and lag gaps and relative speeds. *Accept sufficient size gap.* EV: Target lead and lag speeds and gaps, exit/merge distance. • Change lanes to left or right (McDonald et al. 1997; Brackstone et al. 1998; Wu et al. 2000; Wu et al. 2003). EV: Left-Motivation, opportunity, Right-Pressure, Gap satisfaction.
Strengths		
• Simplicity in modeling the lane changing maneuver. • Considering the whole lane change decision process in one simple stage. • Small number of variables.	• Decide on the basis of maximum gained utility. • Probabilistic results instead of binary answers (yes/no).	• Considering human's imprecise perception. • Calibrating the model with an optimization algorithm. • Finding the fuzzy rules from numerical data.
Weaknesses		
• Difficulties in calibrating the model parameters. • Using primary variables and simple framework to model the lane changing decision.	• Obligation to calculate all probability functions to find the utility of each choice.	• Validation process of the membership functions. • Difficulties and complexity in abstracting fuzzy rules.

4. Limitations of the existing lane changing models

- Current lane change models are mainly related to passenger cars

- No attempt to explore or capture the difference between lane change patterns of passenger cars and heavy vehicles

- Current lane change models are primarily focused on calibrating normal lane change model parameters for heavy vehicles

Existing lane change model

- Focus on the driver's lane change decision

- Largely ignoring lane change execution

- Excluding lane change execution may have a significant impact on expected traffic flow characteristics

4. Limitations of the existing lane changing models

Accuracy assessment of the current lane change model

- Analyzing macro traffic measurements estimated by the model and comparing them to those observed in field data
- Assessing macro traffic measurements is insufficient to test the performance of lane change models

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To further examine the accuracy of the lane change model, the estimated lane change behavior must be microscopically analyzed and compared to the lane change observed in the field data

5. Conclusions and future directions

Rigorous mechanical model

- Create a clear relationship between the explanatory variable and the dependent variable

The fuzzy logic model

- Provide an opportunity to define uncertainty

Three key limitations of the existing lane change decision model

1. – No specific lane change model has been developed for heavy vehicle drivers
2. – Focus on the driver's lane change decision
   - Typically ignoring lane change execution
3. – Macro traffic measurements are used to review the accuracy of the current lane change model

5. Conclusions and future directions

Future research
- Focus on developing micro-traffic flow modeling by providing enhanced capabilities to model the driver's lane change

Points to consider
- Physical characteristics of heavy vehicles
- operational characteristics

Need to develop acceleration/deceleration models for various vehicle types during lane change execution

Requires large trajectory data sets

6. How to apply in drone lane change prediction

- Substitute a spatial equation, I think it would be better to substitute it
- It's a good idea to use fuzzy logic
- Keep thinking about it because it's essential to find the relative distance and relative speed
- More things to think about in order to pick a good traffic context