Autonomous Driving Intelligence System for Safer Automobiles

Hideo Inoue
Kanagawa Institute of Technology (KAIT), TUAT

Pongsathorn Raksincharoensak  Yuichi Saito
Tokyo University of Agriculture and Technology (TUAT)
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Realizing lively and active lifestyle for elderly people
Motivation and objectives: Overcoming fear of driving

- Deterioration in driving ability reduces self-confidence in driving.
- However, elderly drivers are highly motivated to improve QOL.
- Intelligent driving systems can help to compensate for this deterioration in physical ability and overcome the fear of driving.

Drivers over age 60 recognized the warning but did not brake.

Fig. 1 Reaction of drivers to active safety system (Experimental study using Toyota Driving Simulator)

The older the driver, the higher the ratio that could not recognize the warning.

Fig. 2 Vehicle necessity

- Can be used anytime, anywhere
- Trains and buses cannot be used
- Trains and buses limit time
- Trains and buses take too much time
- Love to drive for fun
Our challenge to enhance safety technologies by foresighted driving

Normal driving

- Enhance comfort
- Put to practical use

Risk predictive driving

- Predict and avoid risk
- Not established

Emergency driving

- Avoid collision
- Put to practical use

Accident!!

Establish driving intelligence system to realize risk predictive driving.
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Risk prediction model: Defensive driving, object motion prediction, hazard anticipation

Contour of risk potential generated from surroundings and on-road objects

Driving intelligence must predict the possibility of the appearance of pedestrians from behind an object and determine the optimum safe speed.
Risk predicted motion planning

**Risk prediction**
Repulsive potential form

\[ U_{\text{road}}(X,Y) + U_{\text{obs}}(X,Y) \]

* Risk is determined by environmental states (road and obstacles)

**Motion planning**
Optimization problem for optimal yaw rate calculation

Optimal yaw rate:
\[ \gamma^*(t) = \min_{\gamma_p} J_y(\gamma_p) \]

Cost function:
\[ J_y(\gamma_p) = \sum_{i=1}^{n} [U_{\text{risk}}(X(\gamma_{p,i}), Y(\gamma_{p,i})) + q\gamma_{p,i}^2] \]

**Planned vehicle motion**

- Risks are predicted by environmental states.
- Trajectories of expert drivers can be simulated.
Select the deceleration which results in minimum risk path.

Cost Function Balancing Collision Risk and Vehicle Deceleration (Speed-down)

Longitudinal Control: avoid crash with (virtual) pedestrian

\[ U(X_e(i, j)) = \frac{1}{2} k_{\text{crit}}(X_e - X_s)^2 \]

Risk Potential of Collision with pedestrian

\[ a_x^*(t) = \min_{a_x} \min_{j} \left( U(X_e(i, j)) + r_x a_x^2 \right) \quad 0 \leq a_x(i) \leq a_{x\text{-max}} \]
Risk Potential Based Motion Planning Method

Overtaking a parked car scene  
(Including a rush-out pedestrian)

Risk Potential of obstacle

\[
U_{\text{obs}}(X,Y) = \exp \left\{ \frac{(X - X_o)^2}{\sigma_{xY}^2} - \frac{(Y - Y_o)^2}{\sigma_{yY}^2} \right\}
\]

Risk Potential of road boundary

\[
U_{\text{road}}(X,Y) = 1 - \exp \left\{ \frac{(Y - Y_s)^2}{2\sigma_r^2} \right\}
\]
Risk Potential Based Motion Planning Method

Overtaking a parked car scene
(Including a rush-out pedestrian)

Risk Potential of obstacle

\[ U_{\text{obs}}(X,Y) = \exp \left\{ -\frac{(X - X_o)^2}{\sigma_{X_o}^2} - \frac{(Y - Y_o)^2}{\sigma_{Y_o}^2} \right\} \]

Risk Potential of road boundary

\[ U_{\text{road}}(X,Y) = 1 - \exp \left\{ -\frac{(Y - Y_s)^2}{2\sigma_r^2} \right\} \]

Risk Potential Based Motion Planning Method

\[ U_{\text{risk}}(X,Y) = w_r \cdot U_{\text{road}}(X,Y) + w_o \cdot U_{\text{obs}}(X,Y) \]
Cyber-Physical System: Data-driven A.I. for intelligent vehicles

Low Risk Potential

High Risk

Near-miss incident DB

\[ U_{\text{risk}}(X,Y) = w_r \cdot U_{\text{road}}(X,Y) + w_u \cdot U_{\text{obs}}(X,Y) \]

Low Risk

Medium Risk

Risk High
Hierarchical structure of risk predictive control

1. Basic driving potential to reproduce course collecting of the model driver.
2. Obvious risk potential linked with Data-driven AI
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Near-miss Incident

When Acceleration exceeds -0.45G, driving data are recorded in 10 sec before trigger and 5 sec after trigger.
Traffic Big Data: TUAT Near-miss Incident Database

Annotation

Road type (straight/curved)
Intersection type
Traffic participants density
Number of bars
Pedestrian age
...

Features

Vehicle speed (numerical display)
Turn indicator
Brake
In-room camera
Front-view camera
Camera image switching

Data numbers

Detail of classification

Narrative comments

ID
Safety Cushion

- Unsafe driver

- Careful driver

Adequate adjustments of safety cushion decreases the number of necessary emergency brakes.
Motivation: Adequate Safety Cushion

Conflict: too fast driving: high risk ↔ too slow driving: no driver acceptance

Our motivation is to create adequate safety cushion through machine learning Techniques by taking advantage of past knowledge/experience of near-miss incident.

Driving context + driving behaviour

Hazard potential for road users: ACCEPTABLE

Driver emotion: Context sensitive!

Find the right speed and acceleration ...
Levels of Near-Miss Incident

- **Condition for avoiding a crash**

\[
(D_{\text{car}}(t^*) + D_{\text{ped}}(t^*)) - \left\{ V_{\text{car}}(t^*) \cdot (\tau + SCT) - \frac{V_{\text{car}}^2(t^*)}{2a_{\text{max}}} \right\} = 0
\]

Distance to collision point  
Require distance to stop

\[ \tau : \text{System delay} \]

- **Safety cushion time**

\[
SCT = \frac{\left( (D_{\text{car}}(t^*) + D_{\text{ped}}(t^*)) + \frac{V_{\text{car}}^2(t^*)}{2a_{\text{max}}} \right)}{V_{\text{car}}(t^*)} - \tau
\]

→ Time margin indicator to show near-miss incident level

\[
D_{\text{car}}(t^*) + D_{\text{ped}}(t^*) = \int_{t^*}^{t_2} V \, dt
\]
Factors that Reduce Safety Cushion Time: Conflict Pattern

\[
SCT = \frac{\left( D_{\text{car}}(t^*) + D_{\text{ped}}(t^*) \right)}{V_{\text{car}}(t^*)} + \frac{V_{\text{car}}^2(t^*)}{2a_{\text{max}}} - \tau
\]

Multiple nonstationary

Safety cushion time represents the result of conflict of these factors.

<table>
<thead>
<tr>
<th>Pedestrian behavior ((D_{\text{ped}}, V_{\text{ped}}))</th>
<th>Driver behavior ((V_{\text{car}}))</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="" alt="" /> No road crossing (t_1) (t_2) No road crossing (t_3) Road crossing !!</td>
<td>(V_{\text{car}} a_x) Caution/ careless driver Good anticipation/ No-good anticipation driver</td>
</tr>
</tbody>
</table>

Vehicle dynamics constraints

Stopping distance [m] \(\mu, a_{\text{max}}, \tau\)
The Behavior Models were created for each traffic opponent group (vehicle, pedestrian, bicycle).

- The Behavior Models use the quantified context parameter values (fixed, cannot be influenced) and the quantified driving behavior (can be actively adapted) as input and correlate them with the incident level (criticality of the incident).
- The Behavior Models describe the relationship between the input parameters and are used to predict the resulting incident level.

**Quantified context parameter** ⇒ **Risk values**

**Quantified driving behavior** ⇒ **LHP** (Long-term Hazard Potential)

**Behavior Model:**
Influences of each input parameter and interactions

**Prediction of incident level**
Important Aspects

Near-miss incident database

Context parameter quantification
⇒ Cause and Effect Chain Studies

Annotations

Risk values

Preprocessing

Feature value

Statically processing

Vehicle data

LHP

Driving behavior quantification
⇒ Human Err. Analysis

Test scenario

Preprocessing

Risk values

Machine learning

Level identification

High lev. : 0 < SCT ≤ 1 sec
Mid. lev. : 1 < SCT ≤ 2 sec
Low lev. : 2 sec < SCT

Training data
Proposed index to quantify the driving behavior

Long-term Hazard Potential (LHP)

The index focusing on the speed behaviour from [-10 sec to -4 sec] before the incident.

\[ LHP = w_1 \cdot v_{max} + w_2 \cdot \ddot{v} + w_3 \cdot \dot{v} \]

- Maximum velocity increases LHP with large portion.
- High median of the velocity increases LHP.
- Accelerating situation increases LHP.
- Decelerating situation decreases LHP.
- Large variance of velocity decreases LHP.
Long-term Hazard Potential

\[ LHP = w_1 \cdot v_{max} + w_2 \cdot \ddot{v} + w_3 \cdot \dot{v} \]

Careful driver

Aggressive driver

Speed profile of careful and aggressive drivers is an acceptable trade-off between desired vehicle velocity and driving safety.
Important Aspects

Near-miss incident database

Context parameter quantification ⇒ Cause and Effect Chain Studies

Annotations

Risk values

Statically processing

Preprocessing

Feature value

Vehicle data

LHP

Driving behavior quantification ⇒ Human Err. Analysis

Test scenario

Extraction

Preprocessing

Machine learning

Level identification

SCT

High lev. : 0 < SCT ≤ 1 sec
Mid. lev. : 1 < SCT ≤ 2 sec
Low lev. : 2 sec < SCT

Training data
# Qualitative Context Properties

<table>
<thead>
<tr>
<th>Context properties</th>
<th>type</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static properties</td>
<td>Area type</td>
<td>Residential area/Urban and business area/Rural area/Other</td>
</tr>
<tr>
<td></td>
<td>Road type</td>
<td>Other/One way/Both way</td>
</tr>
<tr>
<td></td>
<td>Sidewalk type</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Intersection type</td>
<td>Other/ T and Y types/ 4 type/ More/ Straight</td>
</tr>
<tr>
<td></td>
<td>Road width</td>
<td>Lanes: other/ 1/ 2/ 3/ 4/ 5 over</td>
</tr>
<tr>
<td></td>
<td>Crosswalk</td>
<td>Without/ With</td>
</tr>
<tr>
<td>Dynamic properties</td>
<td>Parked vehicle</td>
<td>0<del>2/3</del>5/More</td>
</tr>
<tr>
<td></td>
<td>Pedestrian</td>
<td>0<del>2/3</del>9/More</td>
</tr>
<tr>
<td></td>
<td>Traffic</td>
<td>0<del>2/3</del>9/More</td>
</tr>
<tr>
<td></td>
<td>Leading vehicle</td>
<td>Without/ With</td>
</tr>
<tr>
<td>Other properties</td>
<td>Time</td>
<td>6:00<del>10:00/10:00</del>16:00/16:00<del>20:00/20:00</del>6:00</td>
</tr>
<tr>
<td></td>
<td>Weather</td>
<td>Sunny and cloudy/Rain and Snow</td>
</tr>
<tr>
<td></td>
<td>Age of pedestrian</td>
<td>Unknown/Elderly/Mature/Young/Child</td>
</tr>
</tbody>
</table>
**risk value** = \( w_{\text{high}} \cdot f_{\text{high}} + w_{\text{mid.}} \cdot f_{\text{mid.}} + w_{\text{low}} \cdot f_{\text{low}} \)

- \( w_{\text{high}} \) : High level weight
- \( w_{\text{mid.}} \) : Mid level weight
- \( w_{\text{low}} \) : Low level weight
- \( f_i \) : frequency, Order value \( \in [1, 10] \)
SCT prediction model by linear regression analysis

\[ \text{SCT} = \frac{\left( D_{\text{car}}(t^*) + D_{\text{ped}}(t^*) \right) + \frac{V_{\text{car}}^2(t^*)}{2a_{\text{max}}} }{V_{\text{car}}(t^*)} - \tau \]

\[ \text{SCT} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \cdots + \beta_{13} X_{13} \]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient $\beta_i$</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\beta_0$)</td>
<td>4.027</td>
<td>1.083</td>
</tr>
<tr>
<td>LHP</td>
<td>-0.204</td>
<td>0.032</td>
</tr>
<tr>
<td>Area type</td>
<td>0.089</td>
<td>0.045</td>
</tr>
<tr>
<td>Road type</td>
<td>0.023</td>
<td>0.184</td>
</tr>
<tr>
<td>Sidewalk type</td>
<td>-0.045</td>
<td>0.037</td>
</tr>
<tr>
<td>Intersection type</td>
<td>-0.081</td>
<td>0.058</td>
</tr>
<tr>
<td>Road width</td>
<td>-0.035</td>
<td>0.029</td>
</tr>
<tr>
<td>Cross walk</td>
<td>-0.004</td>
<td>0.181</td>
</tr>
<tr>
<td>Parked vehicle</td>
<td>-0.025</td>
<td>0.108</td>
</tr>
<tr>
<td>Pedestrian</td>
<td>-0.028</td>
<td>0.045</td>
</tr>
<tr>
<td>Traffic</td>
<td>0.141</td>
<td>0.085</td>
</tr>
<tr>
<td>Leading vehicle</td>
<td>-0.075</td>
<td>0.034</td>
</tr>
<tr>
<td>Weather</td>
<td>-0.136</td>
<td>0.069</td>
</tr>
<tr>
<td>Time</td>
<td>-0.069</td>
<td>0.026</td>
</tr>
<tr>
<td>Age of pedestrian</td>
<td>-0.086</td>
<td>0.029</td>
</tr>
</tbody>
</table>

$R$-square: 0.137**

N: 600
\[ \text{SCT} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \cdots + \beta_{13} X_{13} \]

\[ \text{SCT} = \beta_0 + \text{Driving behavior} + \text{Driving Context} \]

0.63 sec 4.02 sec -1.16 sec -2.26 sec

controllable uncontrollable

\[ 2 = \beta_0 + \text{Driving behavior} + \text{Driving Context} \]

① **Driver is required to decrease the velocity.**

② **Ref. vel. can be given from the linear regression.**

- Area type: urban area
- Road type: two-way
- Intersection type: T type
- Parked vehicle: high density
- Leading vehicle: without
System Framework

**TUAT Near-Miss Incident Database**

- **Scene classification by traffic opponent:** Vehicle, Pedestrian, Bicycle
- **Driving behavior quantification:** Long-term Hazard Potential (LHP)
- **Context parameter quantification:** Risk Level value for each context parameter value
- **Driving behavior evaluation**

**Real Time Measurement**

- Camera
- GPS, map
- Motion sensor (Speed, Acceleration, Yaw rate, etc.)

**Driving Context & Driving Behavior Sensing**

**Context parameter quantification**

**Safe Speed Computation (Worst Case Scenario)**

\( V_{des} \)  
Safe Speed

(\text{Motion planning}) (Risk potential)

**Quantification of the influence of context parameters and driving behavior on the incident level Behavior Models**
Summary 1: Advanced Safety Vehicle with Driving Intelligence

**Normal driving**
- Car following, Course tracking

**Risk predictive driving**
- Lane Keeping Control
- Cooperative-ACC

**Emergency driving**
- Autonomous Emergency Braking/
  Pre-Crash Safety
- Lane Departure Prevention

**LEVEL 1, 2**

**LEVEL 1**

Source: Toyota
Summary 2: Cyber-physical system for intelligent driving systems

- **Global driving intelligence**
  - Near-miss data analysis/accident analysis
  - Enhanced map for dynamic usage
  - Traffic congestion prediction
  - etc.

- **ICT: Info. & communication technology**
  - V2X

- **Local driving intelligence**
  - ADAS with autonomous driving intelligence

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- Travel conditions database
- Human factor database

Big data

Feedback
Acknowledgement

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