Modeling Driver/Passenger Behavior According to Emotional States for In-Cabin Environment

Eesha Kumar
Pooreumoe Kim
Technische Universität München
Department of Informatics
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Outline

- Introduction
- Behavior Modeling
- Future Work
- Conclusion
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- Behavior Modeling
- Future Work
- Conclusion
Research Question(s)

How can we create/model human behavior from emotional states for In-Cabin Environments?

- What is human behavior?
- What are the major challenges in modeling behavior?
- Why should we model behavior?
- What are some possible approaches?
What is Human behavior?

“In a driving environment, particularly level 3 and 4 semiautonomous, a passenger's behavior is defined by an action performed within the observable environment resulting from an emotional state.”
Why should we model human behavior?

- Human Perspective
  - Safety for human-in-the-loop systems
  - Improve reliability and trust
  - Personalization and adaptability
- Autonomous Perspective
  - Actions as a Quantifiable uncertainty (Human Aware)
What are the major challenges in accurately modeling human behavior?

- Unpredictability in human nature
- One Emotional State can influence Multiple behaviors and/or vice-versa
- Too many unknowns in an environment
- Difficulty in accurately capturing environment data
What are some possible approaches?

- Machine Learning Techniques
- Variational Methods
- Probabilistic Models
- Self Assessments
Outline

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The Big Picture
Kim, Kumar. Modeling Driver/Passenger Behavior According to Emotional States for In-Cabin Environment
Emotion & Affection Recognition

1. Channels
   a. Questionnaire
   b. Electroencephalography (EEG)
   c. Audio
   d. Video
   e. Simulation

2. Techniques
   a. Machine Learning
      i. Conventional
      ii. Deep Learning
   b. Probabilistic Models
Emotion & Affection Recognition - Channels

Questionnaires

- Generating initial labeled data
- Preparing personalized data
Emotion & Affection Recognition - Channels

Simulation

- A popular method to acquire drivers’ data.

- A simulator may involve monitors, and camera to record subjects.

- It also generates artificial sounds to mimic driving environment\(^{[17]}\).
Emotion & Affection Recognition - Channels

**Electroencephalography (EEG)**

- It measures brain activity.

- Bryan James Higgs collected EEG data and use it to his car-following model\(^2\).

- M Soleymani, M Pantic, T Pun measured EEG as well as eye gaze to generate multi-modal model for emotion recognition \(^{14}\).
Emotion & Affection Recognition - Channels

Facial Recognition

- Informative component in emotion prediction.
- Eye Movement/ Gaze analysis improves accuracy\[^{21}\].
- Others measure facial thermometer\[^{12}\].

[A Behavior-based Emotion Recognition System in Intelligent Cars]
Speech Corpus

- A strong tool to measure emotion.
- Hard to collect natural verbal data from simulation (Privacy, etc)
- Researchers classifiers to identify emotions from IEMOCAP and SEMAINE [18].
Emotion & Affection Recognition - Channels

Body Features

- Ishan Behoora and Conrad S. Tucker quantified body parts.
- Labels such as head, right, left arm
- Measured velocity and acceleration of movements for each part \(^9\).
Emotion & Affect Recognition - Techniques

Machine Learning

1. **Conventional**
   a. Support Vector Machines
   b. Random Forests
   c. k-Nearest Neighbors

2. **Deep Learning**
   a. Deep Neural Networks
   b. LSTM Modeling
Emotion & Affect Recognition - Techniques

Machine Learning

1. Conventional
   a. Support Vector Machines
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   c. k-Nearest Neighbors

2. Deep Learning
   a. Deep Neural Networks
   b. LSTM Modeling

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Emotion & Affect Recognition - Techniques

Probabilistic Models

1. Bayesian Networks\(^5\)
2. Probabilistic Product Rule\(^5\)
3. Hidden Markov Models\(^{21}\)
Behavior Modeling

1) Machine Learning
2) Variational Methods
3) Probabilistic models
4) Self Assessment
Behavior Modeling - Machine Learning

- **Why?**
  - Personalization
  - Implicit association of data

- **How?**
  - e.g. K-means classification\(^\text{[1]}\)
    - Predicted trajectory sets by driver’s mental state
    - Match prediction against User Input

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**Driver Mental State:**
- Attentive, partially attentive, or distracted?

**Context:**
- e.g. Right Lane or Left Lane? Entering intersection?

**Environment Classification:**
- K-means

**Associated Prediction Set**
Behavior Modeling - Variational Methods

- Why?
  - No overfitting
  - Various methodologies available

- How?
  - e.g. Model Cost functions to represent disturbance range \(^{[11]}\)
    - Minimise Risk Cost Function
    - Maximise Precision Function
Behavior Modeling - Probabilistic Models

- Why?
  - Mimics Human decision making
  - Quantify Uncertainty in actions

- How?
  - e.g. Maximum Expected Utility\(^5\)
    - Calculate action which maximises utility
    - Generate random actions as follow up
Behavior Modeling - Self Assessment (Manual)

- Why?
  - Ground Truth
  - Generation of Accurate Scenario Data

- How?
  - Questionnaires\cite{11,17}
  - Personal Interviews\cite{4}
Outline

Introduction

Behavior Modeling

Future Work

Conclusion
Future Work

- Non Intrusive Ways to record/sense data
- Further explore Unsupervised Learning and Reinforcement Learning techniques
- Hybrid Integration of Environment’s input sources
- Online Learning
- Portability and Personalization
Outline

Introduction  Behavior Modeling  Future Work  Conclusion
Conclusion

- Behavior modeling remains largely ambiguous
- Past research and implementations
  - Machine Learning Techniques
  - Variational Methods
  - Probabilistic Models
  - Self Assessments
- Tradeoffs
  - Intrusive vs Non Intrusive measurement of data
  - Generalization vs Personalization
Questions
References

Thank you for your time! :)