Classification of obstacles encountered based on drivers' performance and eye behavior

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Introduction

- Autonomous vehicles are developing rapidly. Thus, researchers are trying to design effective autonomous driving systems which is essential to understand human-vehicle interaction.
- Previous researchers have investigated the real-time classification of obstacles during autonomous driving utilizing vehicle sensors [1], but do not fully leverage behavioral measures, such as eye movements, to classify obstacle types.
- **Research Gap**: To use driving performance and eye behavior to classify roadway obstacles that drivers encounter.
- Therefore, the goal of our project was to take first steps toward building classification models using machine learning (ML). These models utilized drivers' performance and eye behavior to predict type of roadway obstacles that drivers needed to avoid.

Data Collection & Processing

- **Participants**: 32 participants, who were students from a research institution [2].
- **Equipment**:
  - National Advanced Driving Simulator (NADS miniSim) (Fig.1) [2].
  - FOVIO FX3 eye tracking system (31x40cm) by Seeing Machines Inc. Canberra, Australia [3].
- **Scenario:** Two-lane rural road with four types of obstacles (an obstacle each type):
  - Small-static object (old tire)
  - Large-static object (construction zone)
  - Small-dynamic environment (rain and wind)
  - Large-dynamic object (deer) [2].
- **Obstacle order**: Determined based on 4x4 Latin Square Design [2].
- **Datasets**: Three datasets were used (data was collected at 60Hz):
  - Driving behavior (miniSim) data
  - Eye-tracking data
  - Combined data.

Fig.1.NADS miniSim used in *N*HanCE lab [4]

Data Collection & Processing (cont.)

- **Windowing**:
  - Calculated when the driver encounters obstacles based on simulation car and obstacles' location from miniSim data. Then we retrieved observation window of 5 seconds (300 frames) before until when driver passed the obstacles (Fig.2).
  - Retrieved and labelled corresponding eye-tracking data based on each miniSim observation windows. As a result, we have three datasets: miniSim, eye-tracking, and combined (Fig.3).

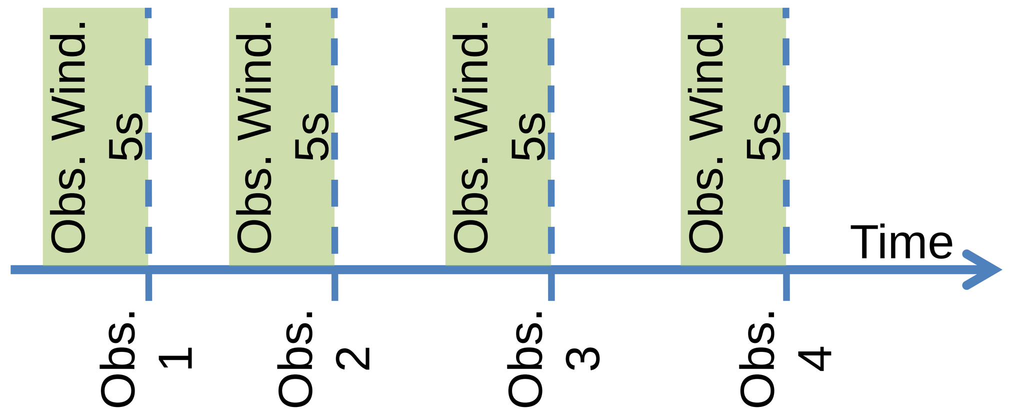

Fig.2.Illustration of observation windows

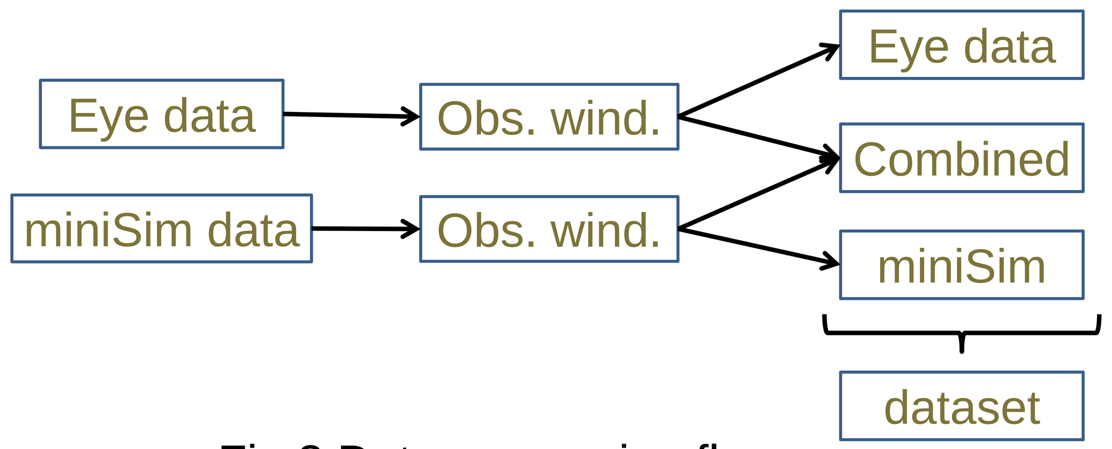

Fig.3.Data processing flow

Modeling Approach

- **Classifiers**: Decision Tree (DT), Random Forest (RF), k-Nearest Neighbors (kNN), Support Vector Machine with linear kernel (SVM_lin) and with radial basis kernel (SVM_rbf), Gaussian Naïve Bayes (NB), and Logistic Regression (LR).
- **Preprocess data**: Divided datasets into training set and test set with the ratio of 7:3. Standardization was conducted following that procedure. Besides, to ensure the fixed results, we use seed of 13 to train-test-split process and models (DT, RF, SVM_lin, SVM_rbf, and LR).
- **Feature selection**: Utilized all features as input, then performed feature selection based on RF's feature importance.
- **Tuning model**: Used GridSearchCV with 3-fold for cross-validation and accuracy as metric.

Modeling Approach (cont.)

- The process of model training and evaluation (Fig.4)

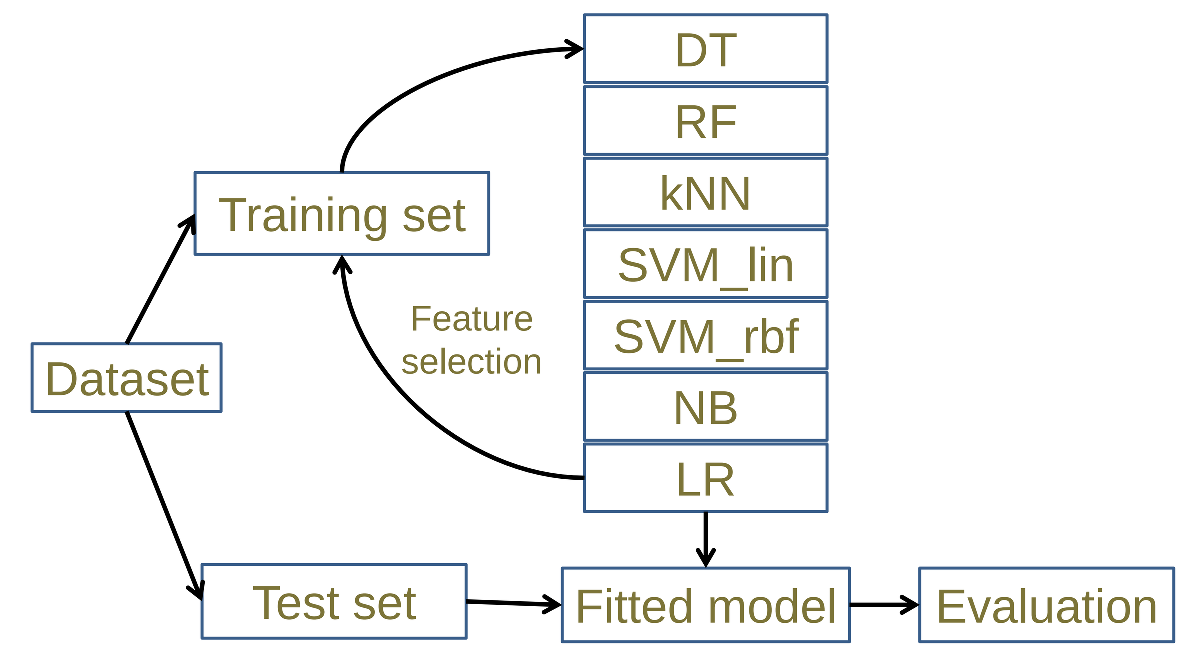

Fig.4. Flow of models training and evaluation

Results

- **Important features** (suggested by RF):
  - Drivers' behavior (top 3):
    1. Vehicle speed
    2. Steering wheel angle
    3. Lane deviation
  - Eye behavior (top 3):
    1. Eye position
    2. Pupil diameter
    3. Eye rotation
  - Combined (top 5):
    1. Vehicle speed
    2. Steering wheel angle
    3. Lane deviation
    4. Steering wheel angle rate
    5. Eye position
- **Results**: Accuracy of each ML approach on each dataset after feature selection .

	Driver Behavior	Eye Behavior	Combined
DT	76.0%	52.7%	75.3%
RF	86.5%	64.3%	88.1%
kNN	82.6%	66.4%	84.2%
SVM_lin	68.8%	45.2%	72.0%
SVM_rbf	85.7%	67.0%	84.8%
NB	63.0%	33.9%	64.9%
LG	68.2%	44.0%	70.5%

Table 1: Accuracy arranged by input measures and ML approaches

Discussion

- The results show that drivers' behaviors are different enough to classify obstacles. For eye behaviors, although they are not distinctive enough for classification, it shows an increase in accuracy in general in the combined dataset.

Conclusion

- Regarding the features from eye-tracking data, we should add features such as fixations count, fixations duration since they relate to mental stress and lane-change intention when drivers encounter obstacles [5] [6].
- Future steps:
  - Adapt the ML models to be integrated into vehicle control to improve conditional automation shared control.
  - Apply models to time-series problems to predict obstacle types encountered.

References

[1] Song, W., Yang, Y., Fu, M., Qiu, F., & Wang, M. (2017). Real-time obstacles detection and status classification for collision warning in a vehicle active safety system. *IEEE Transactions on intelligent transportation systems, 19*(3), 758-773.
[2] Luster, M. S., & Pitts, B. J. (Accepted). *Open-Loop Naturalistic Driving: An Assessment of Human Behavior, Performance, and Physiology to Support Shared Control.* In Proceedings of the Human Factors and Ergonomics Society Annual Meeting.
[3] Luster, M. S., & Pitts, B. J. (2021). A Preliminary Investigation into Learning Behaviors in Complex Environments for Human-in-the-Loop Cyber-Physical Systems. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 65*(1), 42–46. https://doi.org/10.1177/1071181321651222.
[4] The University of Iowa. (2022, May 17). *Simplified Cab Minisim*. Simplified Cab miniSim - miniSim. Retrieved July 19, 2022, from https://www.nads-sc.uiowa.edu/minisim/wiki/index.php?title=Simplified_Cab_miniSim.
[5] Marquart, G., Cabrall, C., & de Winter, J. (2015). Review of eye-related measures of drivers' mental workload. *Procedia Manufacturing, 3*, 2854-2861.
[6] Pan, Y., Zhang, Q., Zhang, Y., Ge, X., Gao, X., Yang, S., & Xu, J. (2022). Lane-change intention prediction using eye-tracking technology: A systematic review. *Applied Ergonomics, 103*, 103775.

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