Identifying Driver's Cognitive Distraction Using Inductive Logic Programming

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Abstract. In our study, we generate rules to determine whether or not a driver is cognitively distracted, using collected data about the driver's eye movements and driving data by Inductive Logic Programming (ILP). We assigned a mental arithmetic task to the research participants to cause cognitive distraction and then learned the rules of the cognitive distraction using the cognitively distracted state as positive examples by ILP. Using the generated rules, we hope to reduce car-driving risks by providing advice or urging caution using voice utterance when distracted driving is detected.

1 INTRODUCTION

We have conducted studies to build a mental model and detect a driver 's tension to develop a safe information service for drivers [3][6]. We generated rules to detect a relaxed state while driving, which is considered the state situation for the information service [3]. However, it is possible that cognitive distraction is included in the relaxed state; therefore, we must detect cognitive distraction to develop a safe information service.

The National Highway Traffic Safety Administration (NHTSA) has identified three types of distracted driving, based on distraction factors[7]: (1) visual distraction, (2) cognitive distraction, and (3) manual distraction. Visual distraction occurs while viewing an unrelated object (i.e., look-away driving). Viewing and operating a smartphone, viewing the car's TV, or operating and viewing the car navigation system are visual distractions. The visibility of outside material (beyond safety checks) during driving is also a visual distraction. Cognitive distraction involves the internal state of the driver who is thinking about unrelated things while driving. Examples include driving while talking on a cell phone and concentrating on one's thoughts. Manual distraction involves an intentionally careless driver. To detect visually distracted driving, we measure the driver's

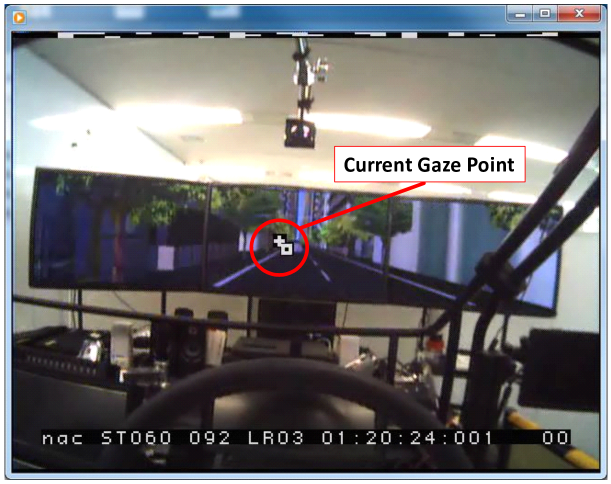

Fig. 1. Simulator environment photographed using the camera of the eye-movement measuring device EMR.

eye movements while driving. However, since cognitive distraction involves the driver 's internal state, it is difficult to detect cognitive distraction using just eye movement and driving data[6].

In our study, we generate rules to determine whether or not a driver is cognitively distracted, using collected data regarding the driver's eye movement and driving data by Inductive Logic Programming (ILP). To generate these rules, we assigned a mental arithmetic task to the research participants to cause cognitive distraction (e.g., Harbluk's method) [1]. In addition, to ensure safety, we used simulation (Fig. 1). Using the simulator, we gathered two types of data: normal driving and driving with a mental arithmetic task as a cognitive distraction. We then learned the rules of the cognitive distraction using the cognitively distracted state as a positive example by ILP. Using the generated rules, we expect to be able to reduce car-driving risks by providing advice or urging caution using voice utterance when distracted driving is detected.

2 EYE MOVEMENT AND DRIVING DATA

2.1 Raw Data

An EMR-8 system was used to collect data on a driver's eye movement. This device measures horizontal and vertical viewing angles in degrees. For the purpose of this study, we consider 60 data points per second.

Using a car simulator system developed by Denso, Inc., we obtained such information as the accelerator depression rate (0% to 100%), braking signal (0 or 1), steering signal (-1 to 1), speed, and GPS information (of the simulator) (60 data points per second).

We gathered eye-movement and driving data on 19 research participants (9 women and 10 men) using the simulator. In our experiment, each driver ran the same 15-minute course two times. The first drive was normal driving (no-load driving), and the second drive was driving with a mental arithmetic task (load driving). The mental arithmetic task involved a two-digit addition problem presented through headphones. We asked the driver the question every uniformity interval. (By one experiment, we made questions for 110 times).

Eye-movement data, car-driving data, and the mental arithmetic task were synchronized, and all data were used to produce background knowledge, as described below.

We defined saccade and fixation as follows [6].

- Saccade
  Saccade is caused by a change in the road situation or the appearance of pedestrians or cars. It is considered a perception factor in the driving model.
- Fixation
  Fixation is a cognition factor in which the driver determines the next action by recognizing changes in the environment and objects. It is also related to the perception of temporal changes, such as signal changes and road signs.

2.2 Data Transformation

We transformed data at constant time intervals to generate qualitative data for ILP learning. We set the intervals at 5 seconds, following the previous study [3]. We generated qualitative data for saccade and fixation information based on the count of the saccade and the length of fixation time during the interval [6], and for other information based on the average in the constant time as in the previous research [3]. Specifically, we transformed eye movement and driving data into qualitative data for use in ILP as follows.

Step 1. Collect a set of raw eye-movement data measured in the time interval, and measure the number of times that saccade and fixation were produced based on eye movement direction and movement distance. In addition, measure the total eye-movement distance.

Step 2. Collect a set of raw driving data measured in the time interval, and average each attribute value of driving data.

Step 3. Integrate the data of Step 2 with that of Step 1.

Step 4. Add new attributes indicating differences in the short time period (5 seconds before) where each difference is represented by Δ-second.

Step 5. Translate the data obtained in Step 4 into corresponding qualitative data using the categories upLow, upMiddle, upHigh, downLow, downMiddle, and downHigh.

3 ILP LEARNING

3.1 Background Knowledge

Table 1 presents a set of predicate types and their mode declarations given to the background knowledge. The first type corresponds to qualitative values for each eye movement and driving data. This is described by the time ID and a parameter value. The second type is a qualitative state difference in a short time (5-second) period and is described as *parameter*_`diff(ID,Val)`. The third one (`before_event`) is used to obtain information of adjacent data.

Table 1. Predicates and their mode declarations in background knowledge. Mode `+` indicates input variable, `-` output variable, and `#` constant.

Types	Predicates
qualitative value	`accele(+ID, #Val)`, `brake(+ID, #Val)`, `velocity(+ID, #Val)`, `steering(+ID, #Val)`, `frontCar(+ID, #Val)`, `gazeX(+ID, #Val)`, `gazeY(+ID, #Val)`, `sacCount(+ID, #Val)`, `fixCount(+ID, #Val)`, `eyeMove(+ID, #Val)`
qualitative state difference	`accele_diff(+ID,#Val)`, `brake_diff(+ID,#Val)`, `velocity_diff(+ID,#Val)`, `steering_diff(+ID,#Val)`, `frontCar_diff(+ID,#Val)`, `gazeX_diff(+ID,#Val)`, `gazeY_diff(+ID,#Val)`, `sacCount_diff(+ID, #Val)`, , `fixCount_diff(+ID, #Val)`, `moveCount_diff(+ID, #Val)`
adjacent saccades	`before_event(+ID, -ID)`

3.2 Training Examples

We used two types of data: normal driving and driving with the distraction of a mental arithmetic task. For the mental arithmetic task, we made questions for one problem every 8 seconds, and measured the time required to answer the questions. We defined cognitive distraction as the driving state during the time it took to answer the mental arithmetic questions and defined this state as positive examples.

3.3 Learned Rules and Discussion

In the present study, we focused on ILP learning using background knowledge and training examples. We generated rules for each individual driver. For example, the rules for research participant F01 (female, 30 years old, driving experience more than 10 years, 5 hours per week or more driving) are as follows.

Table 2 presents the statistics of raw data, transformed data, distracted-driving data (positive examples) and normal driving data (negative examples).

Table 2. Data (research participant F01) used for the experiments

Type	Measured time (second)	Raw data	Transformed data	distracted positive ex.	normal negative ex.
No Task	917	55020	183	0	183
With Task	934	56220	186	119	0

We used our parallel ILP system [5] (based on GKS [2]) to learn rules. We used 8 PCs (total of 36 CPUs). This system generated 22 rules. Learning time was 4615 seconds.

Typical rules are presented below. "{T,F}" denotes the number of positive examples (T) and the number of negative examples (F) covered by the rule.

```
{25,5} class(A) :- front(A, notClear), steering(A, straight),
                   before_event(A, B), front(B, notClear).
```

This is a rule the number of inclusion there were many of the most positive examples and detects the cognitive distracted state using only driving data. This indicates following a forward vehicle and going straight.

```
{23,4} class(A) :- steering(A, straight), eyeMove(A, average),
                   before_event(A, B), front(B, notClear).
{21,3} class(A) :- front(A, notClear), before_event(A, B),
                   steering(B, straight), eyeMove(A, average).
```

These rules correspond to the immediately preceding rule. These rules also considered information on eye moving.

```
{11,1} class(A) :- eyeX_diff(A, rightLow), eyeMove_diff(A, upMiddle),
                                   before_event(A, B), eyeMove(B, average).
```

This rule considers only information on eye movement. Specific eye position and movement are caused to cognitive distraction. In addition, each rule contains the non-determinate predicate `before_event`, indicating the advantage of an ILP-based learner.

For the convenience of learning time, we generated background knowledge data at five-second intervals. In the future, we expect to obtain effective rules with generation at one-second intervals.

In future work, we will implement the generated rules using a GUI system (e.g., Fig. 2) on a tablet PC and will realize distraction detection during driving in real time

4 CONCLUSIONS

In the present study, we generated rules to determine whether or not a driver is cognitively distracted, using collected data about the driver's eye movement

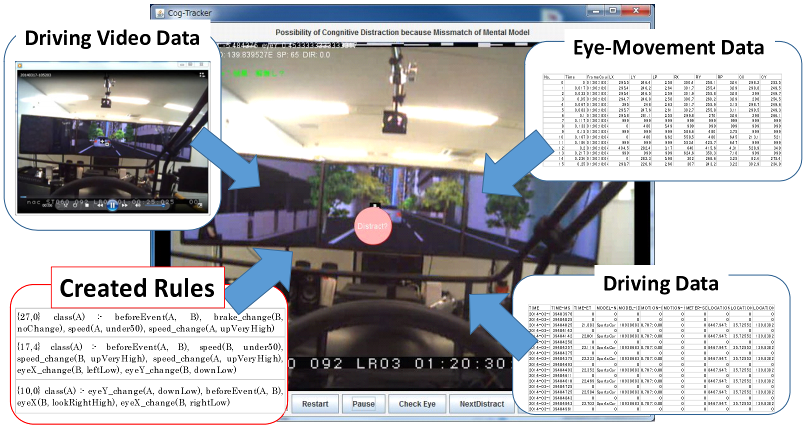

Fig. 2. GUI that enables detection distraction for driving data [4]

and driving data by ILP. We assigned a mental arithmetic task to the research participants to cause cognitive distraction and then learned the rules of the cognitive distraction using the cognitively distracted state as positive examples by ILP. Using the generated rules, we hope to reduce car-driving risks by providing advice or urging caution using voice utterance when distracted driving is detected.

References

1. Joanne L. Harbluk, Y. Ian Noy, Patricia L. Trbovich and Moshe Eizenman: An on-road assessment of cognitive distraction: Impacts on drivers' visual behavior and braking performance, *Accident Analysis & Prevention, Vol. 39, No. 2*, pp. 372-379, 2007.
2. Fumio Mizoguchi and Hayato Ohwada: Constrained Relative Least General Generalization for Inducing Constraint Logic Programs, *New Generation Computing 13*, pp. 335-368, 1995.
3. Fumio Mizoguchi, Hayato Ohwada, Hiroyuki Nishiyama and Hirotoshi Iwasaki: Identifying Driver's Cognitive Load Using Inductive Logic Programming, *Inductive Logic Programming, Lecture Notes in Arificial Intelligence (LNAI), LNAI7842*, pp. 166-177, 2013.
4. Hiroyuki Nishiyama, Akira Yoshizawa, Hirotoshi Iwasaki and Fumio Mizoguchi:Cog-Tracker: A New Tool for Detecting Distracted Car Driving Using Eye-Movement and Driving Data on a Tablet PC, *CATA-2015*, pp.125-130, 2015.
5. Hiroyuki Nishiyama and Hayato Ohwada: Yet Another Parallel Hypothesis Search for Inverse Entailment, *ILP2015*, 2015.
6. Shinichiro Sega, Hirotoshi Iwasaki, Hironori Hiraishi and Fumio Mizoguchi: Qualitative Reasoning Approach to a Driver's Cognitive Mental Load, *International Journal of Software Science and Computational Intelligence 3(4)*, pp. 18-32, 2011.
7. NHTSA: TSA Distracted Driving Research Plan - April 2010 [PDF] DOT-HS-811-299, http://www.nhtsa.gov/Research/Human+Factors/ Distraction