26M-09

「非侵襲型センサーによる運転者の注意散漫行動検出を目的とした認知的負荷の影響の分析」

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＜要旨＞
車を安全に運転する上で、意識を運転に集中させていることは重要であり、運転者が注意散漫状態になる原因としては運転者へ認知的負荷がある。
本研究では、運転者のいくつかのパターンの運転者の注意散漫状態を、運転者の行動から自動的に検出することを目的とする。そのために、実験として複数の状況での運転データ(操舵角やアクセルストローク、車のスピード)を取得し、データマイニングアルゴリズムを適用して解析を行った。
結果として認知負荷の種類によって運転行動が変化することを統計的に示すことができた。 そして、個人ごとの運転行動の変化がそれぞれ別のパラメータに反映されているということを示した。
キーワード:driving awareness, driving behavior, driving distraction, cognitive distraction, cognitive task, time series data analysis

1 研究の概要

Lack of attention or alertness while driving a vehicle is considered to be one of the major reasons of road accidents[1][2]. Recent advances of sensor technology helps researchers to model driving behavior from various sensor data attached to the car and the driver [3]. Automatic detection of distracted driving from driving behavior and issuance of alert can help driver to adhere to safe driving. There are various causes of distraction ranging from driver's fatigue causing drowsiness, sudden health related problems to multitasking with the use of other in-vehicle systems. From various studies, it is known that driving behavior is affected by driver's physical condition as well as cognitive multitasking [4][5][6]. Researches are going on studying for effective detection of driver's distraction from the analysis of driving behavior [7], yet to come up with a successful commercial application.

The effect of distraction and cause of distraction leading to unsafe driving vary substantially from driver to driver depending on driving experience, individual confidence level, age, mental state etc. Thus a personalized modeling of driving behavior and impact of distraction on the model are needed to be studied for developing on-board safety system.

Among varieties of distractions, two major types are visual distraction and cognitive distraction. Visual distraction happens when the driver looks away from the road described as *eye-off-road*, cognitive distraction occurs when the driver's mind is busy with something not directly related with driving known as *mind-off-road*. Visual distraction can be automatically detected by tracking the driver's eye movement. A general algorithm that considers driver's glance behavior across a relatively short period, could detect visual distraction consistently across drivers. Some research works in this direction are presented in [8][9]. However, detecting cognitive distraction is much more complex as the signs of cognitive distraction are usually not straight forward and can vary across drivers. Moreover the driving behavior does not have a simple linear relationship with cognitive distraction. Some studies on cognitive distraction can be found in [10][11][12].

In this work, we restrict our study to the area of cognitive distraction. The main objective of this study is to investigate the possibilities of effective detection of distracted driving from the deviation of the driving behavior of the driver, driving with varying cognitive load. The simulation experiments are done in a driving simulator in different scenarios and multiple drivers are asked to drive 1) with attention without any secondary task 2) with various secondary tasks. The sensors' time series data from driving simulator are collected and analyzed. Statistical tests are done to check whether there is any significant difference between the driving behavior with and without secondary cognitive tasks and what feature or which set of sensor data indicates the most difference during driving with attention and driving with distraction.

2　研究の内容

In this study, we have used driving simulator D3Sim. The driving behavior is assessed from the simulator output which contains time series data (steering angle, steering torque, accelerator stroke, brake stroke, car speed, car angle, engine speed etc.). We have used various scenarios for driving and collected simulator output. The experimental study in detail is as follows:

1) 4 subjects have been used for this study. All of them are students in the age group 20-22 yrs.

2) For each subject, driving data for three situations have been collected: a) normal driving with attention b) driving while continuing conversation with co passenger c) driving while doing mental arithmetic at the elementary school level, such as simple addition, subtraction and multiplication.

3) For each situation, different driving scenarios are used for example, simple route, route having curves and sharp bending and routes with multiple diversions.

4) All subjects are initially allowed to practice for a while in different routes.

5) Each subject is then asked to drive following a car speeding 60km per hour with a more or less constant separation in the designated routes (from simple to complex) consecutively and repeat driving for 5 times.

6) The driving duration in each case was 3 min.

7) The time series output data from the driving simulator for steering wheel angle, steering torque, accelerator torque, brake stroke, car speed and engine speed have been recorded.

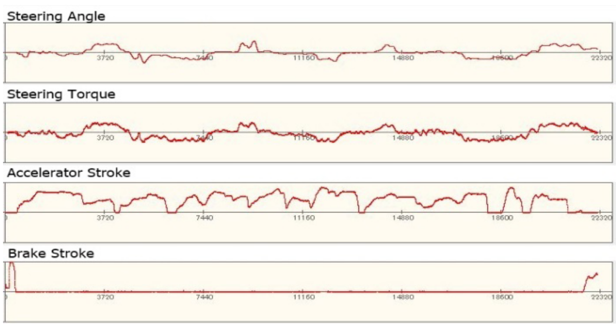

Fig1. Data for normal driving

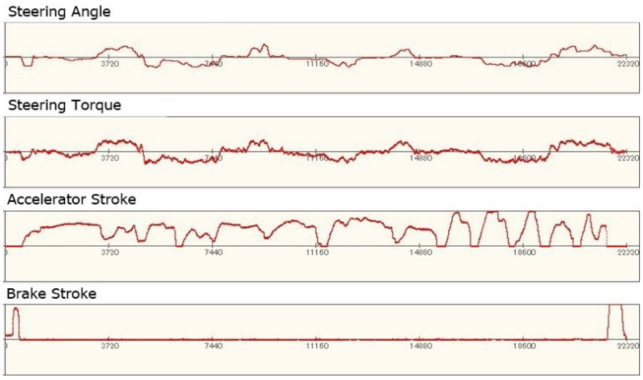

Fig2. Data for driving with conversation

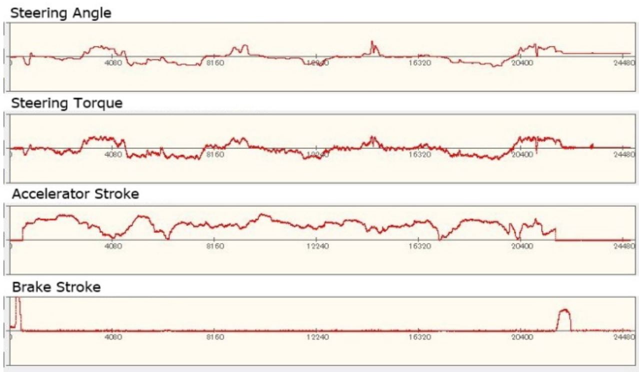

Fig3. Data for driving with mental arithmetic

TABLE I

		Recognized class	
		Normal	With cognitive load
TRUE class	Normal	70.20%	29.80%
	With cognitive load	31.30%	68.70%

TABLE II

1	Feature Number Feature Name
2	Steering Angle SA
3	Steering Torque ST
4	Accelerator Stroke AS
5	Brake Stroke BS
6	Car Speed CS
7	Engine Speed ES
8	Change in Steering Angle D1SA
9	Change in Steering Torque D1ST
10	Change in Accelerator Stroke D1AS
11	Change in Brake Stroke D1BS
12	Change in Car Speed D1CS
13	Change in Engine Speed D1ES

14	Change of Change in Steering Angle D2SA	
15	Change of Change in Steering Torque D2ST	
16	Change of Change in Accelerator Stroke D2AS	
17	Change of Change in Brake Stroke D2BS	
18	Change of Change in Car Speed D2CS	
19	Change of Change in Engine Speed D2ES	

3　これまで得られた研究の成果

In this study we selected 150 driving samples for each person, normal driving 60 samples, driving with conversation 45 samples and driving with mental arithmetic 45 samples. For each sample, 6 time series (steering wheel angle SA, steering torque ST, accelerator torque AT, brake stroke BS, car speed CS and engine speed ES) for 3 minutes are obtained. The data is first preprocessed by using moving average filter and then normalized. The original 6 dimensional time series is extended to 18 dimensions to include first derivative and the second derivative for finding out the best feature subset for individual driver for detection of distraction.

Figure 1, Figure 2 and Figure 3 represent the time series data from driving simulator for different time series for normal driving and driving with cognitive tasks. The horizontal axis represents time in secs. It can be found from visual inspection of the data that steering angle and steering torque show difference in case of driving with or without cognitive load. Moreover it is found that the difference is larger for driving with conversation than driving with simple mental arithmetic.

For initial classification of the time series data in three classes (normal and two types of cognitive loads), the features used from each time series data are maximum value Mk, variance 2 k and average value k as in the following :

$$M_k = max_{1\le t\le N_k}(|y_k(t)|)$$

$$\sigma_k^2 = \frac{1}{N_k}\sum_{t=1}^{N_k}(|y_k(t) - \mu_k|)^2$$

$$\mu_k = \frac{1}{N_k}\sum_{t=1}^{N_k}|y_k(t)|$$

where yk(t); k(= 1; 2; ; 6) is the time series data for *k*th series, k representing each of the 6 time series data collected from driving simulator. Nk, is the number of time intervals from beginning to end of the driving.

Now for every feature and for every series, statistical significance is tested for confirming significant difference between normal and distracted driving. 1NN classifier and SVM with RBF kernel is used to classify the data of driving.

Using the best features from the statistical analysis, SVM is used to classify two classes of driving. Table I represents the results for the best values obtained. We have tried nearest neighbor classifier (1NN) also but we could achieve the average accuracy of classification as 69%.

A. Analysis for Best Feature Subset

In this analysis we used the extended feature set and feature selection algorithms are used to find out the best feature subset for identifying three classes of driving. Table II represents the different dimensions of the time series data collected from driving simulator which are considered to be the features of the driving behavior characteristics. One objective of this study is to find the most important feature subset for individual driver responsible for efficient automatic detection of distraction.

For feature subset selection, Sequential Forward Selection (SFS) and Sequential Backward Selection (SBS) algorithms are used with a wrapper I NN (Nearest Neighbor) classifier with Dynamic Time Warping (DTW) as the distance measure. Table III represents the highest average classification accuracy of three classes driving (normal, with talking and with mental arithmetic) for individual subject with the best feature subset selected by SFS algorithm. Table IV represents the classification accuracy with the best feature subset selected by SBS algorithm. The feature number is described in Table II. It seems that the best feature subset came out to be different for different suboptimal feature selection algorithm. Table V represents the results of another feature selection algorithm CWC developed in [20]. The best feature subset in this case came out to be poor than the other algorithms according to average classification accuracy. Using the best feature subset for individual driver, the average classification accuracy came out to be 77%.

TABLE III

CLASSIFICATION ACCURACY WITH FEATURE SUBSET SELECTION BY SFS

User	Selected Feature Subset	Classification accuracy
1	(3, 6, 9, 8)	0.90%
2	(11,5,1,17,4)	0.80%
3	(11,4,7,5)	0.64%
4	(9,1)	0.67%

TABLE IV
CLASSIFICATION ACCURACY WITH FEATURE SUBSET SELECTION BY SBS

User	Selected Feature Subset	Classification accuracy
1	(8,13,14,15,17,18)	0.93%
2	(5,17)	0.64%
3	(4,13,14,18)	0.64%
4	(3,5,13,15)	0.71%

TABLE V
CLASSIFICATION ACCURACY WITH FEATURE SUBSET SELECTION BY CWC

User	Selected Feature Subset	Classification accuracy
1	(7, 9 ,1 ,4, 6)	0.73%
2	(6, 5, 11)	0.64%
3	(2, 5, 4, 1)	0.71%
4	(3, 11)	0.57%

4 今後の具体的な展開

For future study, we need to integrate other factors influencing cognitive distraction and also use some other sensors to detect cognitive distraction for more concrete results and increased classification accuracy for normal and distracted driving. Also it is found that driving experience has an effect on change of driving behavior with cognitive load. Thus it is worth to study cognitive distraction for modeling personal driving behavior.

5 論文・学会発表等の実績

Basabi Chakraborty, Kotaro Nakano, "Automatic Detection of Driver's Awareness with Cognitive Task from Driving Behavior" 2016 IEEE INTERNATIONAL CONFERENCE ON SYSTEMS, MAN, AND CYBERNETICS OCTBER 9-12 で発表予定

6 受賞・特許

なし

7 参考文献

[1]S. G. Klauer, et al., "The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data", Tech.Rep., 2006.

[2] D. Ascone, T. Lindsay and C. Varghese, "Traffic Safety factor: An Examination of Driver Distraction as Recorded in NHTSA Databases",National Highway Traffic Safety Administration's National Center for Statistical Analysis, 2009.

[3] N. Li, J.J. Jain and C. Busso, "Modeling of Driver Behavior in Real World Scenarios using Multiple Noninvasive Sensors", IEEE Trans. Multimedia, Vol. 15, Issue 5, pp. 1213-1225, 2013.

[4] D. D. Salvucci, "Modeling Driver Distraction from Cognitive Tasks",Proc. 24th Annual Conference of the Cognitive Science Society, pp. 792-797, 2002.

[5] L. Jin et al., "Driver Cognitive Distraction Detection Using Driving Performance Measures", Discrete Dynamics in Nature and Society, Vol.2012, Article ID 432634, 2012.

[6] H. B. Kang, "Various Approaches for Driver and Driving Behavior Monitoring: A Review", Proc. IEEE International Conference on Computer Vision Workshops ICCVW, 2013 pp. 616-623, 2013.

[7] Y. Dong, Z. Hu, K. Uchimura and N. Murayama, "Driver Inattention Monitoring System for Intelligent Vehicles: A Review", Proc. of IEEE Trans. on Intelligent Transportation Systems, Vol. 12, No. 2, pp.596-614, June 2011.

[8] Y. Liang, J. D. Lee and L. Yekhshatyan, "' How dangerous is looking away from the road? Algorithms predict crash risk from glance patterns in naturalistic driving", Human Factors, Vol. 54, No. 6, pp. 1104-1116,2012.

[9] A. Ragab, C. Craye, M. S. Kamel and F. Karray, "A Visual based Driver Distraction Recognition and Detection Using Random Forest", Image Analysis and Recognition, Vol 8814, Lecture Notes in Computer Science,pp. 256-265, 2014.

[10] Y. Liang and J. D. Lee, "A hybrid Bayesian Network approach to detect driver cognitive distraction", Transportation Research Part C, Vol. 38, pp.146-155, 2014.

[11] T. Ershal, H. Fuller et.al, "Model based analysis and classification of driver distraction under secondary task", IEEE Trans. on Intelligent Transport Systems, Vol.11, No.3, pp.692-701, 2010.

[12] M. Kutila, et al, "Driver distraction detection with a camera vision system", Proc. of IEEE International Conference on Image Processing ICIP 2007, Vol.6, pp. 201-204, 2007.

This article is taken from the research paper mentioned in section 5