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Multiclass Classification of Driver Perceived Workload Using Long Short-Term Memory based Recurrent Neural Network

Udara E. Manawadu, Takahiro Kawano, Shingo Murata, Mitsuhiro Kamezaki, *Member, IEEE*, Junya Muramatsu, and Shigeki Sugano, *Fellow, IEEE*

***Abstract*—Human sensing enables intelligent vehicles to provide driver-adaptive support by classifying perceived workload into multiple levels. Objective of this study is to classify driver workload associated with traffic complexity into five levels. We conducted driving experiments in systematically varied traffic complexity levels in a simulator. We recorded driver physiological signals including electrocardiography, electrodermal activity, and electroencephalography. In addition, we integrated driver performance and subjective workload measures. Deep learning based models outperform statistical machine learning methods when dealing with dynamic time-series data with variable sequence lengths. We show that our long short-term memory based recurrent neural network model can classify driver perceived-workload into five classes with an accuracy of 74.5%. Since perceived workload differ between individual drivers for the same traffic situation, our results further highlight the significance of including driver characteristics such as driving style and workload sensitivity to achieve higher classification accuracy.**

I. Introduction

Driving is a dynamic and complicated activity that impose varying amounts of demand on the driver. It involves monitoring the traffic environment, controlling vehicle speed, steering angle, while, in sometimes, operating in-vehicle information systems (IVIS) or engaging in a conversation simultaneously. Driver workload can be identified as the impact on the individual driver resulting from engaging in the driving task in a specific context (i.e., subtask, traffic). Although fully automated vehicles operating in SAE level 5 [1] could eliminate human driver from the control loop, humans will still need to conduct driving tasks until full autonomy is realized. Highly automated intelligent vehicles (operating in levels 2, 3, and 4) with advanced driver monitoring systems that can detect and classify driver workload could provide workload-adaptive support to reduce/optimize driver workload. Such support may include engaging automated driving [2], adapting IVIS parameters, as well as communicating safety-critical information to the driver through human-machine interfaces (HMIs) [3]. Intelligent driver monitoring systems will thus make the roads safer, and driving more enjoyable.

U. E. Manawadu and T. Kawano are with the Department of Modern Mechanical Engineering, Graduate School of Creative Science and Engineering, Waseda University, 17 Kikui-cho, Shinjuku-ku, Tokyo 162-0044, Japan (phone & fax: +81-3-3203-4457; e-mail: manawadu@ieee.org).

M. Kamezaki is with Research Institute for Science and Engineering (RISE), Waseda University, 17 Kikui-cho, Shinjuku-ku, Tokyo 162-0044, Japan. (e-mail: kame-mitsu@aoni.waseda.jp).

J. Muramatsu is with AI system Advanced Development Div., Toyota Motor Corporation, Higashifuji Technical Center, 1200, Mishuku, Susono, Shizuoka, 410-1193, Japan

S. Sugano and S. Murata are with the Department of Modern Mechanical Engineering, Waseda University, 3-4-1 Okubo, Shinjuku-ku, Tokyo 169-8555, Japan (e-mail: sugano@waseda.jp).

URL: htttp://www.sugano.mech.waseda.ac.jp

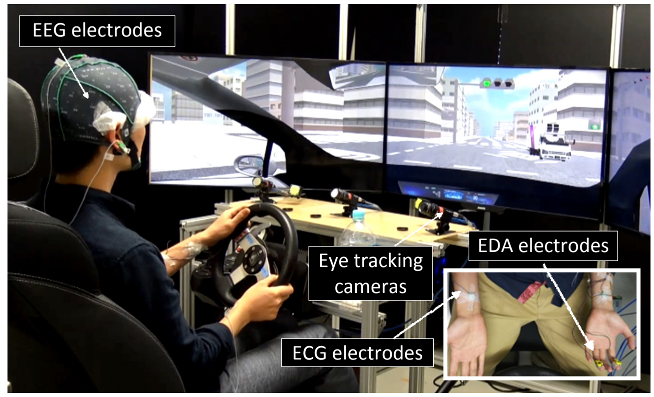

Fig. 1 Driving simulator setup

With more and more people moving into urban areas, traffic complexity in cities and highways will tend to increase. Driver workload is found to be sensitive to traffic complexity. In [4], authors reported that subjective driver workload rating has a linear upward trend with increasing traffic flow. Traffic situation data from onboard database was used in [5] for estimating current driver workload. There are studies on detecting only segments of high workload/stress associated with driving [6]–[8]. However, the number of studies on detecting multiple levels of driver workload is limited. It is important to note that advanced driver assistance systems (ADAS) could adapt their functions according to the level of driver workload. Most of the existing work have focused on detecting driver workload or distraction associated with secondary tasks [9]–[11]. There is a lack of studies focusing on quantifying driver workload attributed to systematically varied traffic complexity levels.

Data collection in real world naturalistic driving, also known as passive data collection, may lead to many problems when creating a computational model [12]. Due to the simultaneous changes in multiple factors, the observed changes in a dependent variable may not be caused by, but still correlated with independent variables. This will result in interactions that are difficult to classify into individual effects. On the other hand, designed experiments can overcome these problems. In a designed experiment, the experimental environment and independent variables are actively manipulated to improve the quality of information and to eliminate redundant data. In addition, data collection is usually done with great care and attention. Driving simulators provide the safety, consistency, repeatability, and ease of a controlled environment. Therefore, in this study, we designed and conducted driving experiments in a simulator.

In order to determine the driver workload corresponding with different levels of traffic complexity, experimental scenarios need to be carefully designed to systematically vary the traffic complexity. In this study, we created a fundamental driving scenario in the simulator based on turning right at an intersection (left-hand traffic) with varying degrees of situational complexity. We recorded physiological, performance, and subjective measures to classify the driver workload in each situation. Nonparametric, nonlinear machine learning models use past data to learn stochastic dependency between past and the future of an observable variable. Artificial neural networks (ANNs) can outperform classical statistical methods, and can be successfully used for modeling and forecasting nonlinear time series data [13]. Conventional Recurrent Neural Networks (RNNs) fail to perform well with long-range time series data due to the vanishing and/or exploding gradient problems. The method we used is Long Short Term Memory (LSTM) based RNN that can overcome above problems [14]. We evaluated the models based on classification accuracy.

II. Related Works on Workload Estimation

A. *Physiological measures and workload*

The human autonomic nervous (ANS) works with the central nervous system to maintain homeostatic conditions and regulates body functions. ANS consists of two divisions that provide physiological responses to stress, fear, relaxation, panic etc. They are: *sympathetic* division which responds to mental stress or physical danger, and the *parasympathetic* system that allows the body to function in a 'rest and digest' state. The ANS responses physiologically to mental stress by accelerating heart rate, dilating pupils, and increasing eccrine sweat gland activity among others [15]. Therefore, by measuring the changes in such physiological indicators, it is possible to quantify driver workload.

1) Cardiovascular measures: Heart rate metrics are frequently used in evaluating operator workload in human-machine systems as they reflect the activities of ANS. Sensitivity of heart rate and heart rate variability (HRV) measures were examined in [16] to distinguish single task driving from periods of secondary workload. It has been found that stress measurements provided by low frequency (LF: 0.04–0.15 Hz) range of HRV correlate well with the mental workload component of NASA-TLX subjective workload assessment tool [17].

2) Electro-Dermal activity (EDA): EDA is also a commonly used indicator for measuring ANS activity. EDA measures include skin conductance level (SCL) and skin conductance response (SCR). Their sensitivity to mental workload in driving has been studied in [6], [18], [19].

3) Pupil size and gaze information: Pupil diameter is used in driving studies as a reliable and sensible indicator of cognitive activity. It is found to have a positive correlation with mental workload. In addition to pupil size, horizontal eye movement is also considered as a good indicator of visual and mental workload [20].

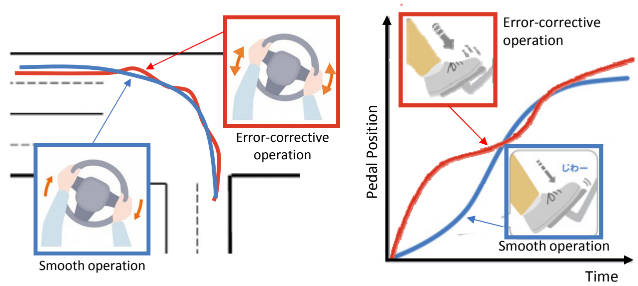

Fig. 2 Performance measures: steering angle and pedal position

Table 1 Workload levels

Level	Description
5 (max)	Workload extremely high: At or beyond the driver's capacity for safe control of the vehicle. No capacity for any additional tasks
4	Workload high: little spare capacity. Level of effort allows little capacity for additional task without compromising the driving task
3	Workload moderate: enough spare capacity for some tasks that have been optimized for the driving situation. Unlimited additional tasks cannot be accommodated.
2	Workload low: sufficient spare capacity for attentional tasks that do not demand continual concentration
1 (min)	Workload insignificant: zero or almost zero driving workload with enough spare capacity for all desirable additional tasks

B. *Performance measures*

Driving performance measures such as steering angle, pedal position, and lane position can provide means to quantify driver workload. Smoothness of steering control is found to have a direct link with perceived driver workload. In the steering entropy method described in [21], the authors showed that steering predictability decreases as drivers make more error-corrective maneuvers, and the frequency and magnitude of the steering corrections increase with the task difficulty. Figure 2 illustrates smooth operation and error-corrective operation of steering angle and pedal position.

C. *Subjective measures*

A range of subjective assessment tools are available to evaluate perceived workloads in human-machine systems. The NASA task load index (TLX) is a widely used assessment tool consisting of six subscales: mental demand, physical demand, temporal demand, overall performance, frustration level, and effort. Another driver workload assessment tool used in the IVIS domain consists of five workload levels: workload insignificant, workload low, workload moderate, workload high, workload extremely high, as listed in Table 1. Subjects with similar personal characteristics are found to respond similarly to tasks with same demand. The Driving

Style Questionnaire (DSQ) and Workload Sensitivity Questionnaire (WSQ) described in [22] have been used in studies to quantify driver personal characteristics.

III. METHODOLOGY

A. Driving simulator

In this study, we used a fixed-base driving simulator, as shown in Fig. 1, described in detail in [23]. Data that reflect the driving behavior and performance were recorded at a sampling rate of 100 Hz. Driver input data consist of steering angle, accelerator and brake pedal position, and turn signals state, while vehicle telemetry data comprise velocity, position and orientation in three-dimensions. Data from vehicle sensors include headway, surrounding obstacle count, types and distances, and lane position.

B. Sensing equipment

We used physiological signal amplifier system PolymateV AP5148[1] to acquire EEG, ECG and EDA signals. It supports sampling rates up to 8 kHz. In order to acquire gaze information, we used Smart Eye Pro[2] gaze tracking system with a 3-camera configuration. It uses pupil and iris reflection with a head model for eye tracking, and has maximum accuracy of 0.5 degrees. Sampling rate is 60 Hz and pupil diameter, eye opening, and gaze position were logged among other parameters.

C. Data acquisition and feature extraction

In this section, we describe the acquisition and processing of physiological signals. We obtained electrocardiogram (ECG), Electro-Dermal Activity (EDA), electroencephalography (EEG), and gaze behavior as driver physiological data. These signals often contain artefacts and anomalies, and therefore, need to be pre-processed. We employ below signal processing methods to increase the overall signal-to-noise ratio with minimal signal degradation.

1) ECG signal: We use a low-pass Butterworth filter with cutoff frequency of 30Hz for ECG signal. We then calculate frequency-domain and time-domain metrics from the filtered signal. To obtain low frequency (LF: 0.04–0.15 Hz) power and high frequency (HF: 0.15–0.40 Hz) power, we use fast Fourier transform (FFT), and then calculate the LF/HF ratio. To obtain the RR interval from the ECG signal, we use a peak detection algorithm and then measure the distance between prominent (R) peaks.

2) EDA signal: For EDA signal, we again use a Butterworth bandpass filter with lower cutoff frequency of 0.5 Hz and higher cutoff frequency of 30 Hz. Then we use an algorithm to detect and replace outliers in the filtered data using linear interpolation.

3) EEG signal: We use a Butterworth bandpass filter with low cutoff frequency of 0 Hz and higher cutoff frequency of 40 Hz for the EEG signal. We then use FFT to obtain the power spectrums corresponding to alpha (8–14 Hz), beta (14–38 Hz), theta (4–8 Hz) and delta (0.5–4 Hz).

We acquire pupil diameter (in mm), eye-opening (0–1), and gaze position (x, y) from the Smart Eye system. The data is already filtered by the system, therefore, did not require preprocessing.

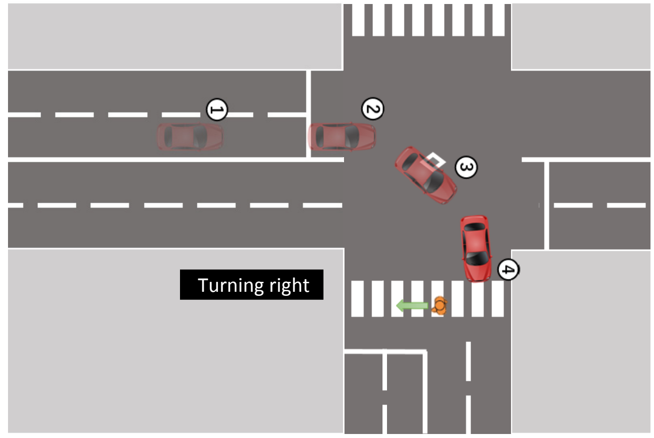

Fig. 3 Driving scenario (left-hand traffic)

Table 2 Experimental conditions

		Pedestrian density (ped./hour)		
		120	240	360
Oncoming traffic flow (vehicles/hour)	120	A	B	C
	360	D	E	F
	720	G	H	I

D. LSTM based recurrent neural network

Recurrent neural networks have recurrent connections between units that allow to exhibit dynamic temporal behavior, and to retain contextual information. However, in practice, conventional RNNs often fail to handle long-term dependencies due to vanishing gradient or exploding gradient problems. LSTM based RNNs can overcome these problems with their capability to retain long-term context. A common LSTM unit, also known as a gated memory cell, consists of an input gate, output gate, and a forget gate. The input gate controls the flow of new values into the cell while forget gate controls the extent to which a value remains in the cell. Finally the output gate determines the extent to which the value in the cell is used in the output of the LSTM cell. In this study we used a deep stacked unidirectional LSTM neural network architectures that specifically use contextual information of the past data. For all architectures we used one dropout layer after the input layer and one fully connected layer before the output layer.

IV. EXPERIMENTAL DESIGN

A. Driving scenarios

In Japan, vehicular traffic moves on the left and turning right at a traffic controlled intersection involves following steps, as shown in Fig. 2. First, turn on the turn signal indicator, drive along the center line of the road and approach the intersection. Secondly, keep the vehicle straight, without turning

[1] http://www.miyuki-net.co.jp/jp/product/catalog/AP5148.pdf
[2] http://smarteye.se/research-instruments/se-pro/

the wheels, and wait to turn right. In the meantime, check for oncoming vehicles, and also the pedestrians, cyclists on the crossing. Thirdly, when there are no oncoming vehicles, proceed cautiously to turn right while paying attention to the opposite lane. Finally, approach the pedestrian crossing slowly, pay attention to pedestrians and cyclists coming from right as well, and proceed cautiously. In order to vary the traffic complexity in each scenario, we defined two variables: oncoming traffic volume, which is the no. of vehicles crossing the intersection in a unit time period, and pedestrian and cyclist density. The experiment consists of the nine (A-I) traffic situations shown in Table 2. We use a pseudo-random order in presenting the traffic situations for each participant.

B. Participants

Fourteen participants (1 female, 13 males) involved in the experiments. Their mean age was 23.5 years and had average driving experience of 3.1 years. Eight of them had previous experience in a driving simulator, and all of them had normal or corrected to normal vision. All the participants received monetary compensation for their contribution.

C. Procedure

The procedure for experiments is as follows. First, we explained the participants regarding the steps in making a right turn and asked them to practice driving and turning maneuvers in the simulator without other traffic nor pedestrians. Then we attached the sensors and asked them to drive along a straight road with minimal traffic and verified the signals acquisition. This was done also to obtain baseline values of their physiological signals and driving performance. After that, for the experiment, they drove along an urban route consisting of the traffic situations listed in Table 2. Soon after making each maneuver, participants input their perceived workload level on a 1 to 5 scale (see Table 1) using a touchscreen interface. After completing all the trials, participants responded to the questionnaires: DSQ and WSQ.

V. Results and Analysis

In this section we present the results from feature extraction, and the classification accuracies of our LSTM based RNN models.

A. Features

Figures 4 to 6 show the normalized SCL, RRI, and prediction error of steering angle for one driver. Note that the sequence lengths are different for individual workload levels due to the difference in times taken by driver to complete the right turn task in each situation. In Fig. 4, we can see a clear difference in the SCL between higher workload levels (4 and 5) and lower levels. Increments in SCL suggest increased sweat gland activity resulting from the arousal of ANS due to high perceived workload. Figure 5 shows higher variability in RRI when perceived workload is high, and vice versa. Acceleration of heart rate indicates the arousal of sympathetic nervous system due to high perceived workload. From Fig. 6 we can see the number of steering angle corrections (peaks),

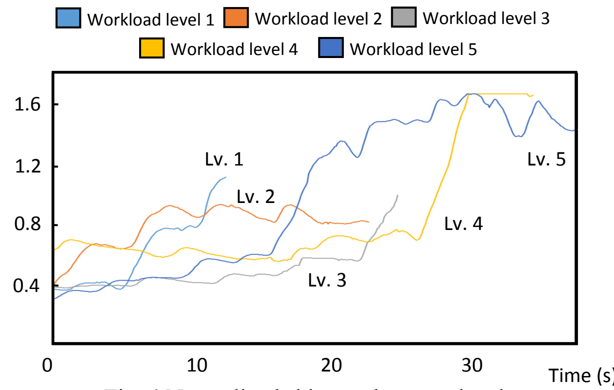

Fig. 4 Normalized skin conductance level

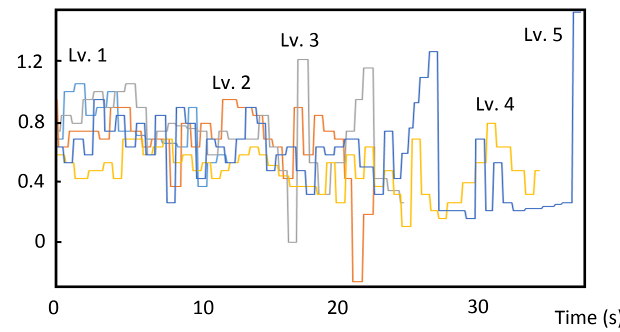

Fig. 5 Normalized R-R interval

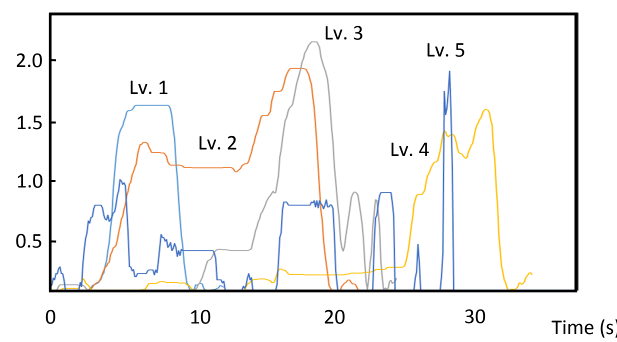

Fig. 6 Normalized prediction error of steering angle

as well as their magnitude increased with the levels of perceived workload. This proves that the smoothness of control input decreases with increasing workload.

B. Classification accuracy

We used 5-fold cross validation approach for model assessment and conducted mini-batch training with batch size of 10. Learning rate was 0.001. We experimented with 50 different model architectures by using different number of LSTM layers and units. The top 5 architectures based on classification accuracy are shown in Table 3. A network with two LSTM layers and 100 units in each outperformed other architectures. Figure 7 shows the system architecture of the driver workload classification system. Confusion matrices showing classification accuracy percentages for each workload level are shown in Figs. 8 (a) and (b). We achieved overall accuracies of 79.8% and 74.5% for training set and test set, respectively.

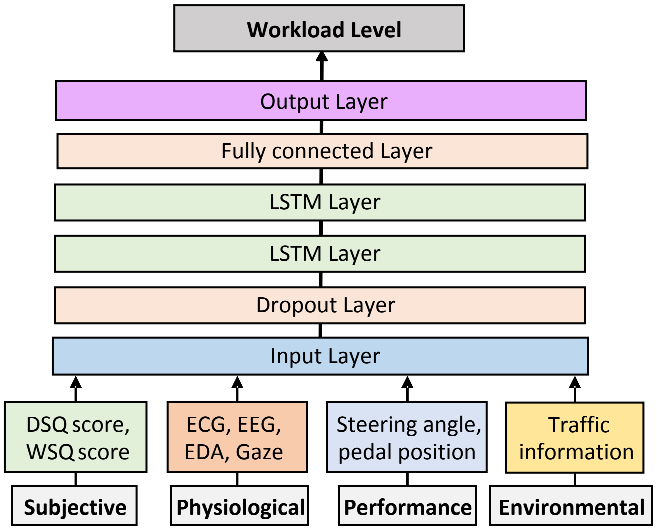

Fig. 7 Architecture of driver workload classification system

Table 3 Classification accuracy of top 5 network architectures (Lxx: L – LSTM layer; xx – no. of units)

Architecture	L50; L50	**L100; L100**	L200; L100	L200; L100; L50	L200; L50; L100
Classification accuracy	0.7766	**0.7979**	0.7819	0.7926	0.7872
Average error	0.0471	**0.0488**	0.0519	0.0491	0.0496
Rank	5	**1**	4	2	3

C. *Comparison*

In order to show the importance of using driver characteristics such as driving style and workload sensitivity as input features, we compared the classification accuracies. When not using DSQ and WSQ scores, as shown in Figs. 9 (a) and (b), the training set accuracy decreased to 70.0% from 79.8%. The test set accuracy significantly decreased to 59.2%, a 15.3 point reduction compared with the model contained personal characteristics.

VI. Discussion

RNN based classification models allow to use dynamic time series data sequences of varying lengths, as opposed to statistical machine learning methods that require fixed sequence lengths. We adopted an LSTM-RNN architecture which outperformed simple RNN architectures, as shown in Fig. 10 (a), due to LSTM's ability to retain long-term context. One limitation in our method is the approach of labelling. When reporting perceived workload levels, drivers may have made errors as we observed they change their initial response in some cases. It is possible that in some situations drivers may have experienced a higher workload level but reported a lower level, and vice versa, hence our training set labels contain human error. We assume this has significantly affected the estimation accuracy of our model. Figure 11 shows

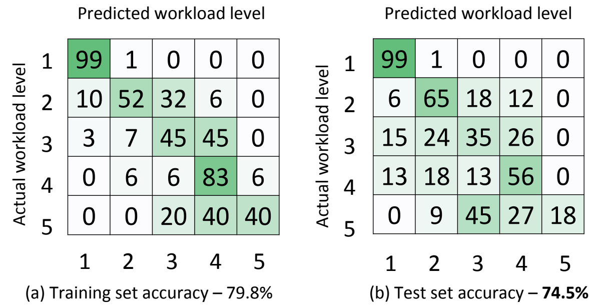

Fig. 8 Prediction accuracies when using personal characteristics

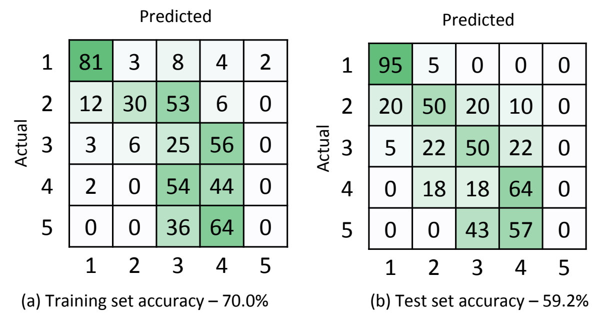

Fig. 9 Prediction accuracies when not using personal characteristics

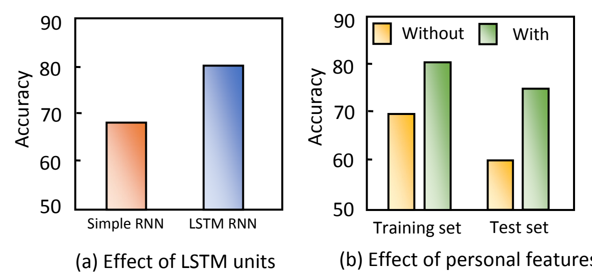

Fig. 10 Comparison of models

the distribution of probabilities for reported workload levels in three traffic complexity levels A, E, and I (out of the nine scenarios described in Table 2). Situation 'A' has the lowest traffic complexity and situation 'I' has the highest, while 'E' lies in between. However, from Table 4, it can be seen that for each traffic complexity level, the reported workload has an average standard deviation of 0.95. Thus, we understand the labelling has an error in the range of ±1. Our model's accuracy increased drastically up to 96.5% when we adopt a tolerance of ±1 for the output workload level.

Perceived workload level for the same traffic complexity (which incur same demand on drivers) may differ between drivers due to individual characteristics related to driving. Our results further show the significance of including driver characteristics such as driving style and workload sensitivity to achieve a higher classification accuracy. Quantifying driver characteristics by using driving style questionnaire and workload sensitivity questionnaire helps to significantly increase the prediction accuracy for new drivers, as shown in Fig. 10 (b).

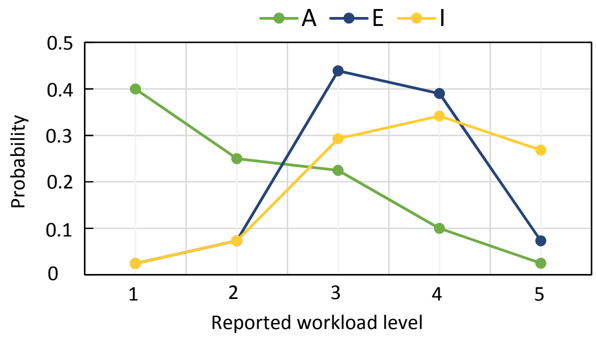

Fig. 11 Reported workloads for three traffic complexity levels

Table 4 Errors in reporting workload levels (labelling)

Average workload	2.1	2.7	2.9	3.0	3.2	3.4	3.4	3.5	3.8
Standard deviation	1.1	0.93	1.1	1.0	0.98	0.71	0.86	0.86	0.97
Traffic scenario	A	D	B	C	G	E	F	H	I

VII. Conclusion and Future Works

In this study we proposed a Long Short-Term Memory (LSTM) based recurrent neural network (RNN) architecture to classify driver perceived workload into 5 levels. Our model takes driver physiological signals including electroencephalography (EEG), electrocardiogram (ECG) and electrodermal activity (EDA), driver performance data including steering and pedal operation, and driver subjective data including driving style and workload sensitivity as inputs. We conducted driving simulator based experiments to create a dataset. By including driver characteristics such as driving style and workload sensitivity, we achieved an overall classification accuracy of 74.5%. Due to personal characteristics, different drivers perceive different workload levels even in the same traffic situation. Therefore, our results show the importance of including individual driver characteristics in predicting perceived workload. Moreover, we understand the human error in reporting perceived workload levels (labelling) has a significant impact on the classification accuracy. By compensating for human error, our model achieved a remarkable accuracy of 96.5%. Future works include experimenting using bidirectional LSTM RNNs and RNNs with attention to further improve the classification accuracy.

Acknowledgments

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