International Journal of Automotive Technology, Vol. 19, No. 5, pp. 895−906 (2018)
DOI 10.1007/s12239−018−0086−0

pISSN 1229−9138/ eISSN 1976−3832

CHARACTERIZING DRIVER STRESS USING PHYSIOLOGICAL AND OPERATIONAL DATA FROM REAL-WORLD ELECTRIC VEHICLE DRIVING EXPERIMENT

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(Received 4 September 2017; Revised 8 March 2018; Accepted 29 March 2018)

ABSTRACT−Electric Vehicle (EV) is becoming a viable and popular option, but the acceptance of the technology can be challenging and lead to an elevated driving stress. The existing studies on stress of vehicle driving has been mainly limited to the non-EVs or survey analysis. In this research, EV driving data of 40 subjects is analyzed, where each subject was asked to drive an EV over a 53 km course in a suburban city of South Korea. Physiological data including electroencephalogram (EEG) and eye-gazing were obtained along with vehicle operational data such as state of charge, altitude, and speed. The dataset was rich in information, but individual difference and nonlinear patterns made it extremely difficult to draw meaningful insights. As a solution, an information-theoretic framework is proposed to evaluate mutual information between physiological and operational data as well as the entropy of physiological data itself. The result shows two groups of subjects, one not showing much evidence of stress and the other exhibiting sufficient stress. Among the subjects who showed sufficient driving stress, 9 out of the top 10 high EEG-entropy drivers were female, one driver showed a strong pattern of range anxiety, and several showed patterns of uphill climbing anxiety.

KEY WORDS : Driver stress, Electric vehicle, Electroencephalogram (EEG), Information theory, Real-world driving

1. INTRODUCTION

Driver stress has been an important topic in automotive research domain, and various types of experiments, data, and analysis methods have been utilized in research. Regarding experiment, simulation and real-world driving are most widely adopted approaches. Real-world driving is obviously more realistic, but it is often constrained with what can be experimented and how much effort it takes. Simulated operation allows robust data collection, but experiments in a closed environment may not fully reflect reality.

For data source, surveys have been an important source of information, where experiment subjects provide direct responses to the questions targeted for the topic of research interest. However, surveys have limitations due to inaccurate human memory, prejudice, personal sensitivity to the question wording, etc. (Visser *et al*., 2000). Alternative data sources, such as video recordings and physiological data, are considered more objective, but the analysis difficulty increases. In particular, physiological data often requires added cost and efforts due to noise and variability of the data (Cannon *et al*., 2012). Unlike the aforementioned data sources, vehicle operational data is readily available from vehicle without requiring additional data generation effort that can interfere with the driving task, and is applicable to a variety of data centric research (Jeong *et al*., 2013; Li *et al*., 2017; Son *et al*., 2016; Wang *et al*., 2016; Xing *et al*., 2018). The downside, however, is that data interfacing and extracting can be painstaking. In the case of EV, we argue that more information fields will be made available in the future, and interfacing will become increasingly less difficult considering the EV's 'electronic-like' aspects (Rahimi-Eichi and Chow, 2014).

In terms of analysis methods, the adoption of highly sophisticated algorithms is often difficult to justify in a driver stress study, due to limited number of subject samples and noisy data sources. It would be more adequate to consider simple statistics analysis or linear models.

There exist numerous literatures on driver stress based on different types of experiments of non-EV vehicles (Table 1). Simulation based experiment, for instance, is utilized to infer driver stress from physiological data including brain activity and heart rate (HR) (Brookhuis and De Waard, 2010), to estimate drivers' mental workload using visual and electrocardiogram (ECG) information using multiple linear regression model (Kawakita *et al*., 2010), and to measure correlation from an extensive set of

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Table 1. Literature on driving workload detection using physiological signals.

Literature	Scenario	Signals used	Subjects	Methodology
Xing *et al*. (2018)	Real-world driving	ECG, SC, ST	10	SVM
Schmidt *et al*. (2016)	Simulated driving	ECG, SC, ST, RESP	46	Correlation
Zhang *et al*. (2015)	Simulated driving, Real-world driving	EEG, EOG	30	LDA
Haufe *et al*. (2014)	Real-world driving	EEG, EMG	20	RLDA
Kim *et al*. (2014)	Real-world driving	EEG	74	Statistical analysis
Lee and Lee (2014)	Simulated driving	EEG	34	Correlation
Lee *et al*. (2014)	Real-world driving	EEG, RESP	20	SVM
Solovey *et al*. (2014)	Real-world driving	ECG, SC	20	DT, logistic regression
Kim *et al*. (2013)	Real-world driving	EEG	30	Statistical analysis
Eilebrecht *et al*. (2012)	Real-world driving	ECG	4	Correlation
Kawakita *et al*. (2010)	Simulated driving	ECG	18	Multiple linear regression
Healey and Picard (2005)	Real-world driving	ECG, EMG, SC, RESP	9	LDA

physiological and operational data as well as survey answers (Schmidt *et al*., 2016). For real-world driving based experiments, electroencephalogram (EEG) data were analyzed to compare driver stress across several urban road sections (Kim *et al*., 2014), survey and video coding data were used to conclude that skin conductance (SC) and HR metrics have high correlations with driver stress (Healey and Picard, 2005), several HR variability measures were compared for detecting driver workload (Eilebrecht *et al*., 2012), and artificial task were imposed on drivers to classify the task and non-task period from using physiological data including HR and skin conductance level, as well as operational data such as steering wheel reversal rates (Solovey *et al*., 2014).

In this study, we extend the results of the previous EV survey studies by exploring physiological data and operational data gathered from a real-world driving experiment. To the best of our knowledge, this is the first analytic study of EV-specific real-world driving data. The analysis, however, turned out to be challenging because of the design limitations on the real-world driving experiments (experiments could not continue to zero state of charge), the large variability in data characteristics over the 40 subjects (for instance, many did not show any sign of stress), temporal changes in stress level (the driving course was made of multiple sections enforcing unique driving environments), nonlinear relationships between data pairs, etc. To cope with those challenges, we selectively choose and pre-process three essential data fields, and adopt information-theoretic analysis methods to evaluate entropies of physiological attributes and mutual information between EEG and three operational data fields.

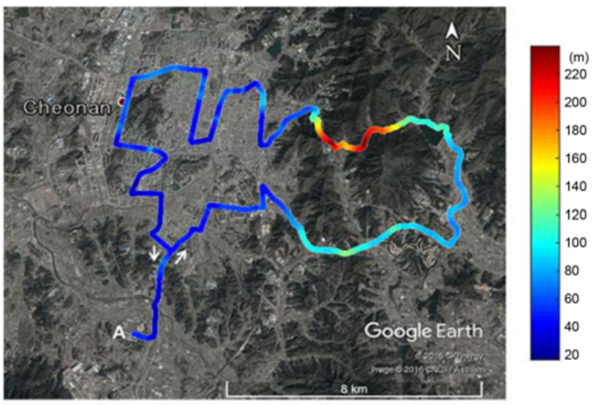

Figure 1. Course map of the experiment. Altitude is shown together in color.

2. EXPERIMENT DETAILS

The driving experiment was conducted in a suburban city of Cheonan in South Korea during off-peak hours, starting around 2PM. The course was 53 km long, and consisted of three segments – rural roads with low traffic, hill segment (maximum altitude over 200 m), and urban roads with frequent traffic signals. Each driver is asked to take a 10-minute break before the urban road segment, and another 10-minute break after the segment. Total driving time ranges from 1.5 to 2 hours. Figure 1 shows the driving route on the map, along with altitude presented in color.

A total of 41 participants (20 males and 21 females) drove the identical route of 53 km on sunny days, one person per day. All 41 subjects had no prior EV driving experience. In the final data set, one male participant was excluded due to a sensor malfunction. For the included 40 subjects, the mean age was 38.4 years and the average

Table 2. Specification of the experiment instruments.

Instrument	Model	Specification	Maker
Test vehicle	RAY EV	Driving range: 91 km	KIA
DAQ module	DEWE-501	8ch analog, 8ch bridge, 2ch CAN	Dewetron
GPS	NL-3020	Reacquisition : 0.1s	navilock
Gyro	MTI	Rate: 300 deg/s, Acceleration : 5G	XSENS
Camera	HDCAM-1600UVC	2 mega-pixel, 30fps	KRIZER
Inverter	HT-S-1200-12	1200W, DC 12V	Izzy power
Laserscanner	ibeoLUX	0.3 ~ 200 m	ibeo
Eye tracker	Smart eye 5.9	3ch camera CAN out	Smart eye
Bio measure	Poly G-I	16ch Analog out	LAXTHA
Monitoring S/W	DEWE Soft	Ver 7.0.3	Dewetron

Table 3. List of data chosen for analysis.

Data field		Sensor	Sampling rates
Physiological data	EEG (8 channel)	PolyG-I	250 Hz
	Eye-gazing	Smart eye	60 Hz
Operational data	State of charge	Vehicle CAN	10 Hz
	Altitude	NL-3020	1 Hz
	Velocity	NL-3020	1 Hz

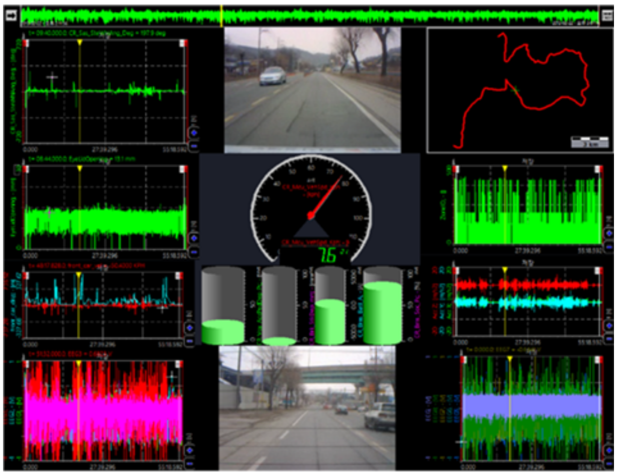

Figure 2. Monitoring system used during the experiment. The display was made available to the backseat researcher.

driving experience was 11.9 years. The EV used in this experiment can be driven 91 km with a full charge, and the initial State-Of-Charge (SOC) was 85 % on average at the beginning of the experiment. Physiological data was collected using dedicated sensors attached to the subjects, and an eye-tracker was installed. To collect operational data, a collection system interfacing CAN (Controller Area Network) was used. Multiple cameras, along with an external GPS, were installed, too. Specifications of the installed instruments are listed in Table 2. Before the experiment started, the base data of each driver was collected for one minute. During the base data collection, the engine's ignition was kept off. The experiment was monitored in real-time by a researcher sitting on a backseat, and the monitoring system shown in Figure 2 was used.

3. DATA PROCESSING AND EEG

Among the collected data fields, we first selectively chose the most essential ones. The list of selected data fields and their original sampling rates are summarized in Table 3. EEG signals were measured and collected by electrodes that were attached to the subjects. Eye-gazing data was collected by installing two eye-tracking cameras on the dashboard. Velocity and altitude were extracted from the GPS data, and SOC values were obtained through CAN embedded in the vehicle.

As anticipated, the raw data from the experiment was not adequate to apply in the analysis, and required extensive pre-processing and sanity check. EEG and eye-gazing data were windowed to 1 Hz. From eye-gazing data, fixation frequencies were extracted and filtered to mid-panel and right-panel areas, where remaining driving range (RDR) value and SOC information were displayed respectively. Altitude data had somewhat large variance, and it was corrected for every longitude and latitude combination by taking the median value of all 40 drives. RDR was displayed on the dashboard but was not collected from the vehicle, and was estimated using the state of charge value and vehicle fuel efficiency. In our analysis, RDR is used as a proxy of SOC since SOC value was not available directly to driver while RDR was. In Figure 3 (a), a sample of pre-processed data is plotted for subject #21.

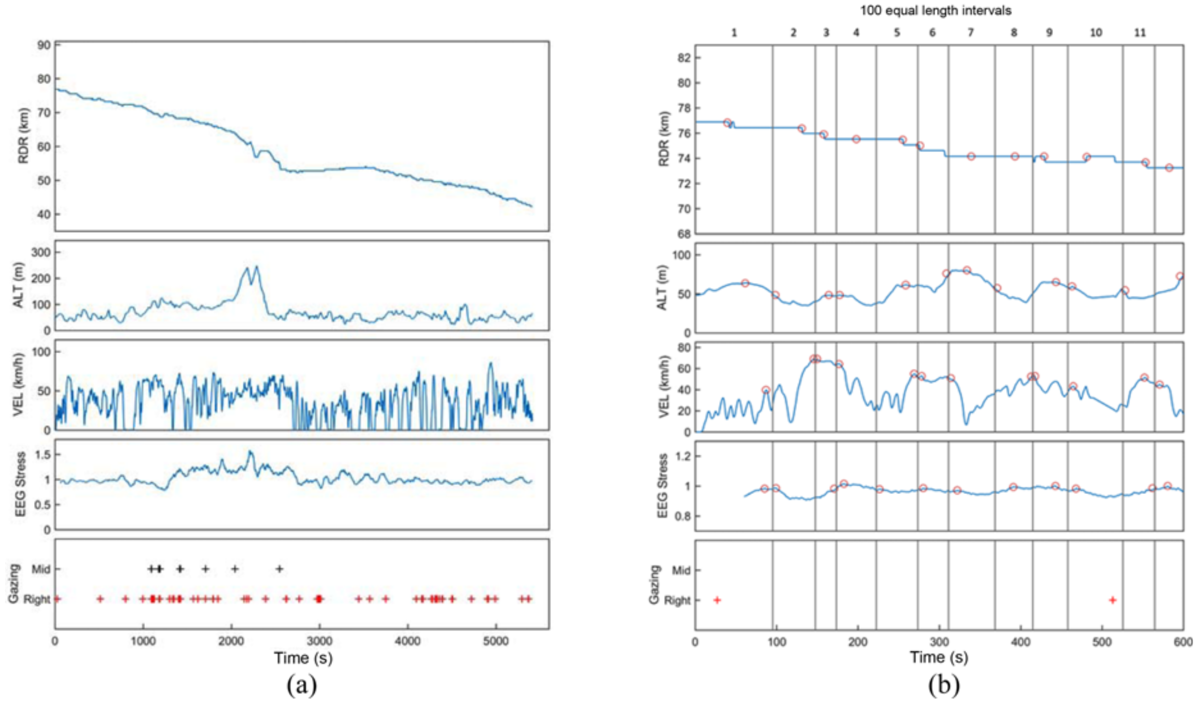

Figure 3. (a) Sample of pre-processed physiological and operational data (subject #21); (b) Aggregation of the data into the 100 equal-distance intervals (Sample of first 600 seconds shown).

To evaluate entropy and mutual information, each subject's data was aggregated into 100 intervals by dividing the driving route to 100 equal-distance intervals. An example is shown in Figure 3 (b) for the first 600 seconds of subject #21's driving. For each of one-percent progress interval, the maximum observed data value was chosen as the representative value. We chose the maximum because we are interested in the relationship for the large value situations such as high altitude, high velocity, high EEG, etc. Flow diagram of data pre-processing is presented in Figure 4.

EEG waveform consists of several types of brain waves that have different frequency bands, which represent various dominant mental states such as sleep, awake and tension (Andreassi, 2013). In our experiment, eight electrodes were attached to the head surface following the international 10-20 system as shown in Figure 5 – two on frontal lobes (F3, F4), two on temporal lobes (T3, T4), two on parietal lobes (C3, C4) and two on occipital lobes (O1, O2). The two frontal lobes electrodes in particular, were attached to F3 and F4 to reduce eye motion related noise. The EEG signals were collected with a sampling rate of

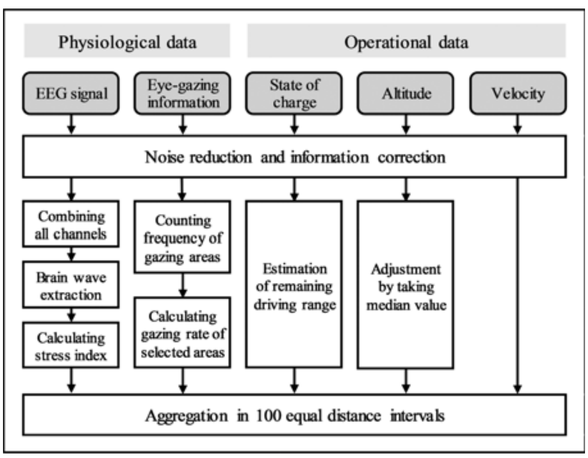

Figure 4. Data pre-processing procedure.

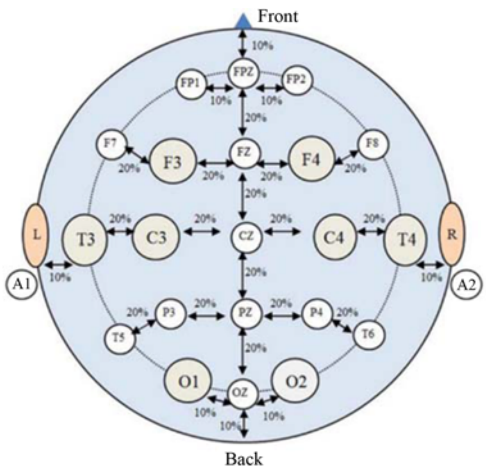

Figure 5. International 10–20 system of electrode placement (Kim *et al.*, 2014).

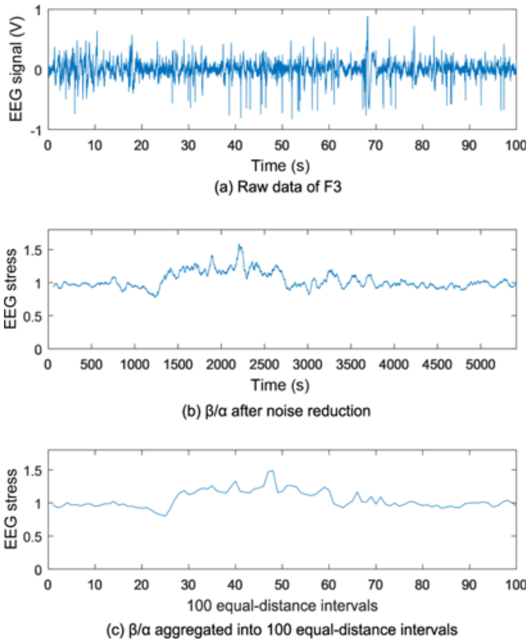

Figure 6. EEG data preparation example of subject #21: (a) Raw data of F3; (b) β/α after noise reduction; (c) β/α aggregated into 100 equal-distance intervals.

250 Hz, resulting in 150 MB of data for each driver. Due to the nature of EEG data collected in multiple frequency bands, it required extensive preprocessing to extract relevant information (Lee and Lee, 2014) (Figure 6). Upon applying noise reduction by smoothing, short-time Fourier transformation (STFT) technique was applied to separate the EEG waves into the different frequency bands (Lee *et al*., 2017). In the process of STFT, we used a hamming window of a half overlap with the previous window, and the window length of two seconds. By averaging the value of power within the ranges of the brain waves, individual brain wave's relative power was calculated for each moment. Among the multiple EEG waves, we used β and α waves to generate EEG stress index in our analysis, which is the ratio of β and α waves. The β/α ratio is one of the commonly used EEG indexes representing stress since beta waves are activated when a person feels stressed or busy, and alpha waves are activated when they are relaxed (Kim *et al*., 2013). In this study, we used a ratio of the half-beta wave (13 ~ 23 Hz) to alpha wave (8 ~ 13 Hz) as the stress index to identify subjects' actual stress in EV driving. Half-beta wave was chosen to excluded vehicle electric noise frequency of 24 ~ 30 Hz related to engine secondary vibration (Kim *et al*., 2014; Zhang *et al*., 2015).

4. ENTROPY AND MUTUAL INFORMATION

When investigating relationship between two variables, evaluating Pearson correlation coefficient is a simple and popular method. The evaluated value, however, can be misleading, since it only measures linear relationship and lacks the capability to measure nonlinear relationship. Mutual information is a powerful and accurate measure for such relationship, and it is chosen as the main analysis method in this study.

4.1. Shannon Entropy and Mutual Information (MI)

Claude Shannon established the foundations of information theory with his seminal paper that was published in 1948 (Shannon, 2001). Information theory provides advanced tools for quantitative analysis of information, and entropy and mutual information (MI) are two of the most fundamental concepts in the theory (Cover and Thomas, 2012). They are widely used in many research fields because the concepts provide a formal way to quantify information of random variables and their associations. When an event is likely to happen with probability p_A and indeed the occurrence of the event is observed, the amount of information generated from the observation (data) can be defined as $I(A) = \log\frac{1}{p_A}$. If the logarithmic function is base two, then the unit for information quantity is in bits. This definition by Shannon shows that observing an event that has a smaller probability of occurrence provides more information, which is in line with intuition. For a random variable X, the expected information gain by obtaining a single observation can be evaluated as the expected value of $I(X)$, and can be written as below.

$$H(X) = E\left[\log\frac{1}{p(x)}\right] = -\Sigma_{x\in X}\, p(x)\log p(x) \tag{1}$$

Here, H(X) is defined as entropy. It can be easily shown that entropy is nonnegative and has the maximum value if and only if $(x_i) = \frac{1}{n}$, for all i. A more uniform distribution means that it has a higher uncertainty, and thus the value of one observation is the maximum in terms of obtaining information from the observation of outcome. In this work, a random variable with high entropy indicates that the data source is useful and provides new information as we obtain more observations. On the other hand, a random variable with close to zero entropy indicates that almost no information can be provided with an additional observation.

While entropy is defined for a single random variable to quantify its information amount, mutual information is defined for two random variables to quantify their mutually shared information amount. Therefore, by obtaining one observation of the first random variable, one can extract information of the other random variable in the amount of mutual information value. Formally, mutual information of random variable X and Y is defined as below.

$$I(X;\, Y) = \Sigma_{x\in X}\, \Sigma_{y\in Y}\, p(x, y)\, \log\frac{p(x, y)}{p(x)p(y)} \tag{2}$$

Because mutual information is defined based on the distributions, and not based on the observed values, it captures the relationship between the two random variables in an ideal way. Even if the relationship between the observed values are nonlinear, mutual information can still clearly evaluate if observing one random variable is helpful for understanding the other random variable. This is the reason why we have chosen mutual information in this work instead of Pearson correlation coefficient or any other measure. In fact, we have analyzed the EV data using Pearson correlation coefficient and many other advanced analysis techniques, but eventually had to resort to mutual information because no common pattern emerged over the 40 drivers and the techniques we tried were not very effective. Entropy and mutual information turned out to be a good match for extracting the underlying information of our EV data.

4.2. Binning Approximation of Mutual Information

When sample observations of continuous random variables are available, calculating entropy and MI is nontrivial because their underlying probability distributions need to be evaluated first (Kinney and Atwal, 2014). This is the main reason why entropy and mutual information are not as popular as they are supposed to be. When one is interested in approximation of the information amount instead of the exact amount, however, there is a simple and widely used trick of binning. Binning approximates a continuous distribution by partitioning the support of a random variable into a fixed number of equal size bins (Kraskov *et al*., 2004). By adopting binning, entropy is approximated as

$$H(X) \approx H_{\mathrm{bin}}(X) = -\Sigma_{\mathrm{i}}(i)\ \log p(i) \quad (3)$$

where $p(i)$ is the fraction of data (observations) in i'th bin of X, which is the ratio of the number of data points in i'th bin to the total number of data points. In the same way, approximating MI is carried out as

$$I(X;\ Y) \approx I_{\mathrm{bin}}(X;\ Y) = \Sigma_{\mathrm{i}}\Sigma_{\mathrm{j}}p(i,j)\ \log\frac{p(i,j)}{p(i)p(j)} \quad (4)$$

where $p(i, j)$ is the fraction of data in the intersection of i'th bin of X and j'th bin of Y, which is the ratio of the number of data points in the intersection to the total number of data points. When the number and range of bins are carefully chosen, the binning method can provide very accurate approximations.

4.3. Application of Entropy and Mutual Information to Our Data

In this work, we calculate entropy of each EEG and eye-gazing attributes, respectively, and MI between EEG and each of the three operational data fields in Table 3 using binning approximation. First, each attribute is partitioned into a finite number of bins in the range between the minimum and the maximum values of 40 subjects' data. The reason why the range of the entire subjects, not the range per individual subject, is used for all subjects is because we are interested in comparing the subjects. If a subject's EEG hardly changes relative to the other subjects' EEG changes, we'd like to have a low entropy value calculated for the subject. With a careful analysis, the number of bins is determined to be 10. After the bins are fixed for each attribute such as EEG, we estimate each individual subject's data distribution using the bins, and calculate entropy of EEG and gazing. Then, MI between EEG and each of RDR, altitude, and velocity is calculated.

Besides the approximation of binning, there is another limitation in our approach. The entropy calculation in Equation (1) assumes that data samples are drawn independently. EV data, however, was collected in time sequence and therefore relationship among nearby samples exists. Such a relationship reduces the amount of new information that can be provided by the next sample, and

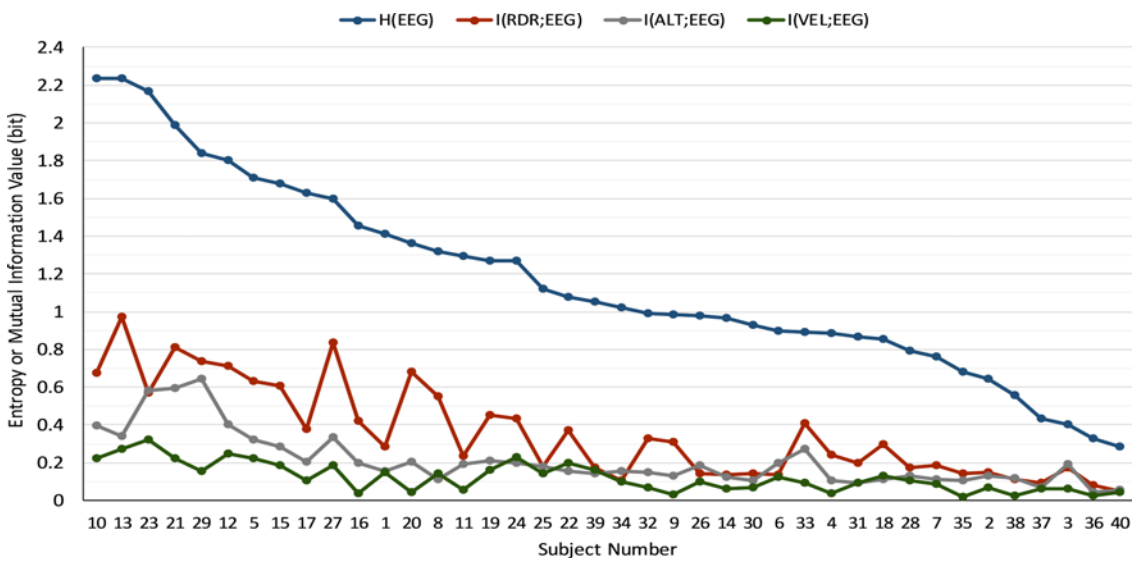

Figure 7. Entropy and mutual information chart in order of H(EEG).

Table 4. Entropy, mutual information values and subject information.

Subject number	H(EEG)		I(RDR;EEG)		I(ALT;EEG)		I(VEL;EEG)		H(Gazing)		Gender	Age (yr)	Driving Exp. (yr)
1	1.414	(12)	0.287	(21)	0.154	(30)	0.148	(14)	0.542	(2)	M	45	20
2	0.647	(35)	0.151	(30)	0.130	(20)	0.068	(28)	0.222	(15)	F	50	15
3	0.402	(38)	0.176	(28)	0.192	(21)	0.063	(29)	0.081	(25)	M	54	21
4	0.887	(29)	0.241	(22)	0.104	(34)	0.037	(36)	0.000	(32)	M	28	7
5	1.709	(7)	0.631	(8)	0.324	(8)	0.220	(7)	0.327	(13)	F	42	15
6	0.898	(27)	0.134	(35)	0.201	(27)	0.124	(18)	0.515	(4)	F	31	2
7	0.764	(33)	0.183	(25)	0.111	(26)	0.085	(25)	0.161	(21)	M	48	20
8	1.317	(14)	0.553	(11)	0.114	(17)	0.145	(15)	0.366	(9)	F	52	21
9	0.986	(23)	0.308	(19)	0.128	(38)	0.032	(37)	0.000	(32)	M	55	17
10	2.237	(1)	0.675	(7)	0.398	(4)	0.221	(6)	0.000	(32)	F	57	19
11	1.294	(15)	0.236	(23)	0.194	(16)	0.057	(32)	0.081	(25)	F	25	2
12	1.802	(6)	0.709	(5)	0.403	(6)	0.248	(3)	0.194	(17)	F	29	3
13	2.234	(2)	0.972	(1)	0.340	(10)	0.270	(2)	0.462	(6)	F	30	10
14	0.965	(25)	0.138	(34)	0.126	(33)	0.060	(31)	0.222	(15)	M	27	8
15	1.678	(8)	0.608	(9)	0.288	(7)	0.188	(9)	0.426	(8)	F	25	6
16	1.457	(11)	0.419	(14)	0.198	(18)	0.040	(35)	0.366	(9)	M	57	10
17	1.631	(9)	0.381	(16)	0.207	(9)	0.107	(19)	0.446	(7)	M	40	17
18	0.854	(31)	0.296	(20)	0.114	(22)	0.130	(17)	0.194	(17)	F	30	5
19	1.270	(16)	0.452	(12)	0.209	(15)	0.162	(12)	0.081	(25)	F	44	7
20	1.365	(13)	0.684	(6)	0.204	(19)	0.046	(33)	0.081	(25)	F	30	5
21	1.991	(4)	0.812	(3)	0.597	(2)	0.224	(5)	1.135	(1)	M	34	11
22	1.076	(19)	0.371	(17)	0.154	(37)	0.199	(8)	0.286	(14)	M	31	13
23	2.171	(3)	0.569	(10)	0.584	(1)	0.320	(1)	0.000	(32)	F	53	17
24	1.270	(17)	0.433	(13)	0.198	(12)	0.229	(4)	0.141	(23)	M	28	9
25	1.124	(18)	0.181	(26)	0.179	(13)	0.142	(16)	0.081	(25)	F	29	11
26	0.981	(24)	0.143	(31)	0.184	(24)	0.099	(21)	0.194	(17)	F	44	15
27	1.601	(10)	0.838	(2)	0.336	(5)	0.186	(10)	0.081	(25)	F	30	10
28	0.794	(32)	0.176	(27)	0.133	(28)	0.103	(20)	0.475	(5)	M	49	20
29	1.837	(5)	0.734	(4)	0.642	(3)	0.153	(13)	0.000	(32)	F	43	12
30	0.931	(26)	0.142	(32)	0.105	(23)	0.071	(26)	0.000	(32)	F	23	1
31	0.869	(30)	0.201	(24)	0.093	(29)	0.091	(23)	0.366	(9)	M	45	20
32	0.992	(22)	0.330	(18)	0.146	(25)	0.069	(27)	0.366	(9)	M	25	7
33	0.893	(28)	0.411	(15)	0.270	(11)	0.091	(24)	0.526	(3)	M	32	12
34	1.024	(21)	0.103	(37)	0.154	(32)	0.099	(22)	0.194	(17)	F	43	20
35	0.680	(34)	0.140	(33)	0.104	(35)	0.016	(40)	0.161	(21)	M	32	11
36	0.327	(39)	0.081	(39)	0.041	(40)	0.023	(39)	0.081	(25)	M	31	10
37	0.436	(37)	0.095	(38)	0.070	(31)	0.062	(30)	0.141	(23)	M	47	19
38	0.557	(36)	0.112	(36)	0.117	(14)	0.027	(38)	0.000	(32)	F	30	10
39	1.051	(20)	0.174	(29)	0.142	(36)	0.163	(11)	0.000	(32)	F	33	10
40	0.286	(40)	0.051	(40)	0.058	(39)	0.040	(34)	0.000	(32)	M	53	7

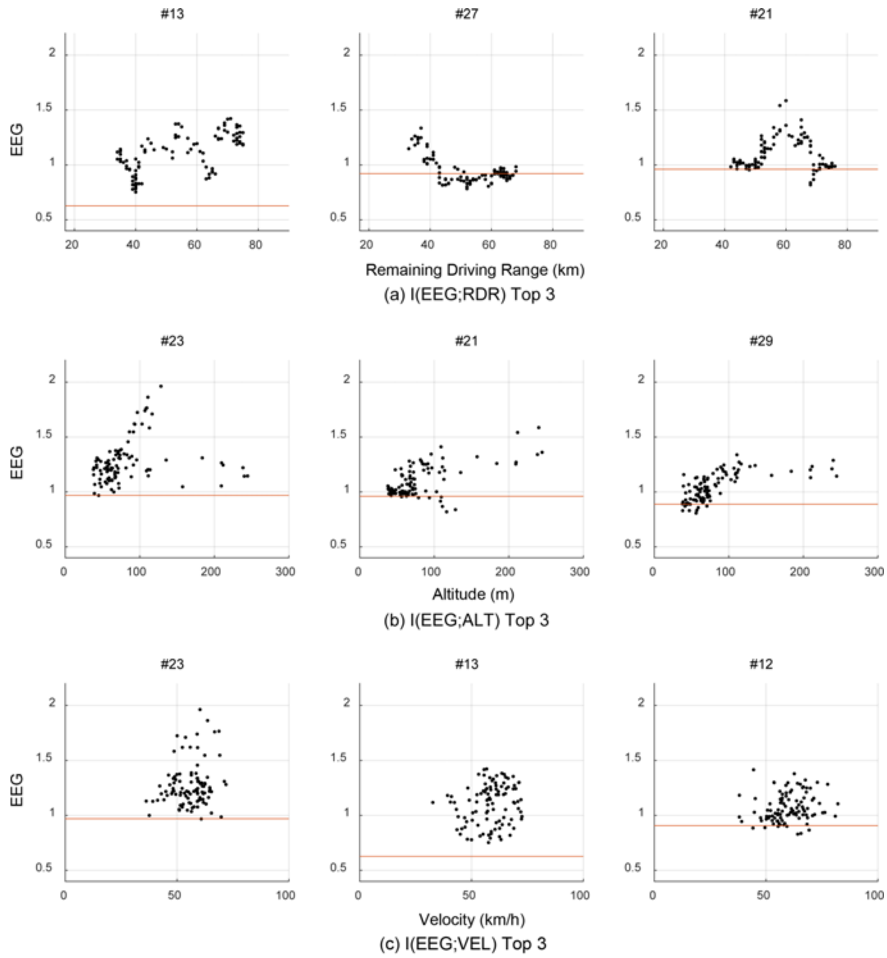

Figure 8. Scatter plots of the top 3 subjects with the base values of EEG stress index (horizontal lines). The base data of each driver was collected before the driving started: (a) Top 3 for I(RDR;EEG); (b) Top 3 for I(ALT;EEG); (c) Top 3 for I(VEL;EEG).

therefore the entropy and mutual information we calculate are somewhat larger than the true values. Nonetheless, our focus is on the relationship analysis of physiological data and operational data, and the limitation does not make much difference on the results that are presented in the following section.

5. ANALYSIS RESULTS

Using the 100 intervals explained in Section 3, each subject's data was organized in 100 rows, where each row contained the maximum EEG, eye-gazing, RDR, altitude (ALT), and velocity (VEL) values of the corresponding interval. Entropy and MI were then calculated for all 40 subjects using the binning technique explained in Section 4. The results are summarized in Table 4 with driver's gender, age, and driving experience information.

The entropy and MI values are summarized in Figure 7. We observe that entropy of EEG ($H(EEG)$) ranges from 2.24 bits to 0.29 bits. Considering that uniform distribution over 10 bins corresponds to entropy value of 3.32 bits and that 3.32 is the upper bound, 2.24 indicates that EEG values are highly variant over 100 intervals for subject #10. On the other hand $H(EEG)$, value of 0.29 indicates EEG values are almost constant over the 100 intervals for subject #40. In total, 19 subjects had less than 1 bit of $H(EEG)$, suggesting that they experienced almost no stress during driving, or the physiological sensors failed to capture their stress. This issue is further addressed in the discussion section.

Another interesting finding is that 9 out of the top 10 high-entropy drivers were female. Overall, female drivers accounted for roughly half (21 out of 40), and '9 out of 10' strongly implies that female drivers might be more subject to driving stress, possibly to EV driving in particular. Although further study is needed to validate such hypothesis, gender gap seems to be a strong candidate to characterize individual difference in driving stress. On contrary, age and driving experience did not show a meaningful relationship.

When eye-gazing data's entropy was evaluated, the values were far lower than those of EEG. This implies that eye-gazing data collected in the experiment is not capable of capturing driver's stress. MI between eye-gazing and each of the three vehicle operational data fields was also evaluated, but they were also too small to draw any meaningful conclusion. Note that low MI values were expected since entropy is the upper bound of MI.

The 100-interval data are plotted for all 40 subjects. Each set of plots is the pairwise combination of EEG, and RDR, ALT and VEL. The top 3 MI subjects were extracted from Table 4, and the associated plots are presented in Figure 8. In Figure 8 (a), RDR plots of top 3 subjects clearly show EEG patterns that are dependent on RDR. In particular, subject #27's EEG stress index climbs up as the RDR becomes less than 45 km, and this corresponds to a pattern of range anxiety. Range anxiety is a psychological state of stress or fear regarding the uncertainty of the next charging opportunity, and it is known as a phenomenon that happens to the less experienced EV drivers (Franke *et al*., 2012; Nilsson, 2011; Rauh *et al*., 2015). The corresponding subject, however, happens to be the only driver exhibiting a very strong pattern of range anxiety. Subject #21's EEG-RDR plot shows a pattern that is highly related to climbing uphill section of the driving course. As expected, this subject appears in top 3 of EEG-ALT plots included in Figure 8 (b). Subject #13 shows the largest $I(RDR; EEG)$, but its EEG change pattern is difficult to interpret. The strange pattern might be related to the range anxiety and altitude, but effect of other stressors, whether directly related to driving or not, cannot be excluded. In Figures 8 (b) and (c), the top 3 subjects for EEG-ALT and EEG-VEL are shown respectively. Unlike the EEG-ALT plots where some subjects show clear pattern in the climbing uphill section, EEG-VEL plots exhibit fairly random behavior in the top 3 group.

The subjects who have low $H(EEG)$ show almost no change in EEG value compared to the base value measured when they were not driving. Clearly, EEG data did not contain any interesting signal related to stress for those drivers. Note that we performed data validation for the drivers with large entropy values, by playing back the entire driving video clips to detect major distraction or interruption, and nothing unusual was found.

6. DISCUSSION

Understanding the stress of driver has been an important and widely researched topic for many decades. As EV becomes popular, the driver stress studies need to be carefully repeated for EV. Such EV-specific studies are still in its early stage, and the existing stress studies are heavily focused on survey data. In this work, we used real-driving data of 40 subjects to study driving stress of EV.

Our results suggest that the relationship between physiological data and operational data is specific to the individual driver, which coincides with the results of previous research (Eilebrecht *et al*., 2012; Healey and Picard, 2005; Schmidt *et al*., 2016; Solovey *et al*., 2014). Some drivers showed prominent relationship when measured with mutual information, especially for the pairs of (EEG, RDR) and (EEG, ALT). As for the RDR and the related range anxiety, a pattern of range anxiety was found for only one subject, but the pattern was very strong. As for the ALT and the related uphill climbing anxiety, EEG sensor data showed noticeable change during the driving experiment for many drivers. Cross-examination with the course characteristics and video records confirms the uphill climbing anxiety of the drivers.

The real-world EV driving data was rich in information. In fact, besides the data fields that were used in this study, many other operational data fields including acceleration pressure and braking pressure were available. Despite of the richness of the data, the EV stress analysis using physiological data and operational data was quite challenging. The analysis had to be done purely based on the collected sensor data, and no human feedback or survey records from the drivers was available. Without such additional information, identifying the important data fields and proper relationships were difficult due to the individual difference. Even when meaningful relationships existed, they were typically nonlinear, making widely-adopted analysis methods, such as correlation study, to fail. For dealing with the individual difference and the nonlinear relationships, our framework of dividing the course into 100 equal-distance intervals and adopting information theoretic measures turned out to be very effective. We were able to successfully analyze the sensor data and identify range anxiety and uphill climbing anxiety, and furthermore discover that 9 out of top 10 high EEG-entropy drivers were female. We believe our framework of analysis is quite effective and useful for many studies that are based on real-world driving data.

Because of EV's inherent nature of utilizing electricity and electronics, it is expected to have an excellent capability for collecting operational data related to the driving environments and control records. Even today's EV's collect numerous data fields for a variety of purposes, and future EV's are very likely to have even stronger storage, network-connectivity, and data utilization capabilities. In contrast to the operational data, it is not clear if physiological data of human bio-signals will be ubiquitously available. To obtain high-quality bio-signals, high-end physiological sensors need to be carefully attached to the driver and the contact needs to remain stable despite of the driver's movements. Therefore, it would be best if useful information such as driver stress can be extracted only from operational data, without using physiological data. In this study, however, we actually used both of physiological data and operational data to investigate the stress of EV driving. The positive part of our study is that our analysis of physiological data and operational data showed the large potential of using sensor data for stress analysis. Then, the next question is how to move on from here to detect driving stress using operational data only. One possible solution might be to look for general trends. This study was limited to only 40 subjects, but if the physiological plus operational data study can be extended to a much larger number of drivers, one might identify strong general trends. In such a case, the knowledge on general trends can be utilized together with operational data. When operational data shows a pattern that is known to be strongly related to a type of driver stress, the stress can be detected with a high accuracy without using physiological data. Another possible solution might lie in the individual characterization. Our study shows that individual patterns are strong among the 40 drivers. If each individual's stress data pattern is consistent over repeated driving, the individual's physiological data may be collected only for once or a few times and be used for producing the knowledge about the driver. Then, the personalized knowledge can be stored for the future use with the driver's real-time operational data to detect the stress. The ideas might be too early, and future research is needed to find the best ways to take advantage of operational data.

The framework and some of the findings in our study are not only limited to EV studies, but they can be applied to other tasks such as developing handover policy of autonomous driving. For SAE level 2 and 3 of autonomous driving (SAE On-road Automated Vehicle Standards Committee, 2014), for instance, handover between driver and vehicle is required. For such a handover, inferring driver psychological state from the vehicle operational data can be critically helpful, and the psychological state can be used to decide whether the driver is ready to drive. Therefore, we can think of a scenario where an unexpected incident occurs and automated driving system (ADS) utilizes the driver's psychological state information derived from the operational data to decide when and how to handover.

A few limitations exist in this study. First, despite of the study being focused on EV, range anxiety was detected only for one driver. This may be due to the limitation of our real-world experiment where the remaining driving range was not pushed all the way down close enough to zero, or due to the influence of the experienced researcher who was riding in the back-seat all the time. In any case, shortcomings in the experiment setup and data collection might have limited us from identifying range anxiety of other subjects. To overcome such a limitation, more careful examination of sensor setup would be helpful, and even detailed surveys and interviews in addition to the video recordings could be utilized for checking ground-truth of driver's psychological state. Simulator experiment can be adopted in the study, too.

Secondly, more than half of the subjects didn't show noticeably high entropy for EEG, and therefore the associated mutual information that is upper bounded by entropy was very small, too (Cover and Thomas, 2012). The result can be interpreted in two different ways. One might conclude that there is a specific group of people who are more susceptible to driving stress, and that only their driving stress can be inferred using physiological data and the relevant operational data. On the other hand, one might also argue that the sensors might have been loosely attached and thus hindered an effective data gathering. If the latter is true, drivers showing no sign of stress need to be excluded from the study. Even in this case, however, our methodology and analysis results on the individuals with sufficient stress still remain valid and correct. The last limitation is the pre-processing of physiological data. In the case of eye-gazing data, it was found to be hardly usable despite of trying numerous known pre-processing methods. However, there might have been a better pre-processing or coding scheme for the way eye-gazing data was collected in our experiment. For instance, individual calibration of the eye-gazing data might been helpful, but no data was collected for the calibration purpose.

Lastly, the extent of EV specific driving stress in each subject's EEG response is difficult to identify. Further study to compare our results with those of conventional carbon-fuel vehicle driving experiement on the same course might be necessary to provide critical insights on commonality and diversity between conventional and electric vehicle driver workloads.

7. CONCLUSION

In this study, we investigated a rich set of real-world EV driving data and proposed an analysis framework to infer driving stress including range anxiety and uphill climbing anxiety. To the best of our knowledge, this study is the first non-survey data analysis of real-world EV driving. The proposed information-theoretic framework enables quantitative analysis of physiological and operational data by properly handling individual difference and nonlinear patterns. A few interesting results were found, and the possibility is open for utilizing the framework for future real-world EV driving data and autonomous driving data. For EV, we believe use of operational data will be an important and practical goal, and the implications of this study were discussed. Overall, extensive future research efforts are required on various aspects, and authors believe that this study made an important contribution by conducting a data-driven analysis and by suggesting critical factors to consider in the future endeavors.

ACKNOWLEDGEMENT–This research was supported by a grant (17TLRP-B131486-01) from Transportation and Logistics Research Program funded by Ministry of Land, Infrastructure and Transport of Korean government.

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