DRIVER'S WORKLOAD DETECTION FOR ADVANCED DRIVING ASSISTANCE SYSTEM

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A thesis submitted to the Nanyang Technological University

in partial fulfilment of the requirement for the degree of

Master of Engineering

2018

Acknowledgement

I hereby acknowledge that this work has started with support from BMW-NTU joint lab, under supervision of Professor Huang Guangbin, my supervisor. And from October of 2016 onwards, I was supported by RR@NTU Corp lab. Thanks to all these parties that made this available till present.

My supervisor, Professor Huang Guangbin has opened an opportunity for me in NTU, Singapore. He is also a pioneer researcher and has exposed me to the cutting-edge development of technologies. Also he has encouraged me not to give up the work and trusted me. I happily offer great appreciation to him.

Thanks to Dr. Yang Yan, who was project leader and is now professor at Northwestern Polytechnological University, Xi'an, China. She has guided me into research field of Human Machine Interface (HMI) studies and advised on domain knowledges.

Thanks to Professor Seah Hock Soon and Professor Lin Feng. And also the thanks go to current and former project managers: Dr. Wang Yi, Dr. Gee Sen Bong, Dr. Wang Xuan and Dr. Goh Chi Keong. They have offered me to RR@NTU Corp lab and also encouraged me to keep on the study, and also willingly provided advices in many aspects.

I also thank my former colleagues: Liyanaarachchi Lekamalage Chamara Kasun, Liu Tianchi, Cui Dongshun and many others. They were my partners during study and research. Also, they provided me encouragement.

Lastly, I give thanks to Rebecca, my wife, who always was by my side. And my mother and my father (who rests in heaven), who inspired me to pursue this career. Also thanks to my brother and sisters of lovely Singapore Church and my heavenly Father.

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Abstract

Advanced Driving Assistant System (ADAS) was developed to reduce hazard on road, as drivers tend to get distracted from non-driving tasks. Researchers widely acknowledge that machine learning should be applied in ADAS, so that system can recognize driver's state and adapt accordingly. Applying machine learning to physiological signals to learn psychological model is a common research topic. Yet, little work has considered the challenges in implementation, which is different from other machine learning domains. Usual approach is to collect many signals and go through tedious signal processing to output feature vectors. Machine learning plays its part only after features are available, which is costly and unlikely to be feasible in real world situation. We propose new machine learning based methods that only require simple single signal combined with manifold learning algorithms. Our methods are robust in that they require only one signal but don't compromise the performance.

The first contribution of the work is that we collected data from partly automated vehicle's simulation, where machine learning has seldom been applied. The second contribution is that we proposed new feature extraction methods which only exploit ECG signal. Our methods do not require domain specific knowledge or tedious signal processing procedure. As long as intervals between R peaks are available (which can be measured easily with cheap commercial equipment), our manifold learning based feature extractor will provide reliable features. As this implies no pre-processing, it is more beneficial for implementation.

Keywords: *ECG, Machine Learning, Driver, Workload, ADAS. Manifold learning*

1. Introduction

1.1. Motivation

Vehicle driving is a complex task. It is commonly accepted that distraction or stress to the driver can be highly hazardous[1], [2]. To compensate risks from these human errors, some vehicles were equipped with Advanced Driving Assistant System (ADAS)[3]. ADAS is a system that assists vehicle control. ADAS could include several functionalities, such as adaptive cruise control (ACC). ACC enables the vehicle to control lateral and longitudinal movement by itself to follow the lane or preceding vehicle and is currently implemented on some commercial vehicles. Vehicles equipped with such functionalities yet sometimes require human driver’s intervention. The reason is that there are some situations that commercial system cannot recognize: red traffic light or pedestrians crossing the street. In these situations, drivers are required to ‘take-over’ the control of the vehicle. Thus, it is still recommended for the driver to be adequately focused on driving.

As ADAS are introduced, drivers became more prone to be engaged in non-driving tasks. Also drivers in a highly automated vehicle were found to be suffering from boredom[4]. ADAS should be adaptive to driver’s conditions, in other words, the workload should be maintained in optimum level[5] by ADAS. Yet, human factor has not been well studied in the context of driving assistance. It is a rational direction of development to enable ADAS to assess driver’s conditions and adapt to it accordingly. On this perspective, methodologies to model driver’s state and how to make the system recognize the state has to be studied.

1.2. Previous Works

There was a work of workload adaptive cruise control from Hajek et al[5]. It revealed that adaptation for the workload is beneficial for ADAS. Yet recognition of workload was manually operated by the human experimenter in the study. They asserted that new generation of ADAS must take account of driver's psychological state to dynamically response accordingly.

Healey et al. conducted a real driving experiment[6], which came out to be phenomenal work in driver's stress recognition. They developed wearable computing module that can collect various physiological signals during real-world driving. Signals they measured were: electrocardiogram (ECG), electrodermal response (EDR), electromyogram (EMG) and respirations (Resp). Feature extractor was applied on those raw signals via 5 minutes windowed filter. The feature vectors were analyzed with linear discriminant function. According to experiment protocol, features taken from segments where the driver was taking rest before and after driving was labeled low; segments where the subject was driving on the highway was labeled medium; and segments where the subject was driving in the city area was labeled high. Overall recognition accuracy was 95%. Furthermore, they analyzed the correlation between feature and expert-ratings of stress. They stated the significant features related to stress. And heart rate turned out to be in 2nd place; the correlation coefficient was 0.6.

Trained model needs to be robust in many kinds of variations. Variations can occur between subjects and between days[7]. Variation can even occur when human might response less to same stimuli or when they are exposed to stimuli repeatedly[8]. Solovey et al[9]. conducted a real-world driving study which aimed to resolve this variation. Two experiments were done in the work. They had recruited 25 subjects for data collection. Collected data were heartrate and CAN bus data. Subjects were asked to perform N-back task while driving. Using collected data, various machine learning algorithms were trained. Other periods were labeled as baseline and N-back task period was labeled as elevated workload. With new experiment from 100 subjects they successfully classified workload elevation across subjects.

Through surveying previous works, it is safe to conclude that driver's psychological state can be clearly detected by machine learning algorithms. When some environments or situations affect vehicle driver, then sensor data collected from driver can be fed into machine learning system to detect the psychological state. Yet, in most cases they tended to increase the number of sensors which is only suitable for laboratory setting. We believe that when this is to be applied in real world situation, there will be other issues that need consideration. So we expect that in real world situation, it is more suitable to design system that only uses single signal.

1.3. Objectives

Integrating driver's state assessment and driver assistance system can be a great breakthrough, which will lead to significant enhancement to driver safety. This work focuses on advancing the techniques to assess vehicle driver's psychological model applicable in real world situation. To enable interactions with ADAS, detection methods need to output result in real-time. In common lab experiments, after data collection is completed, which is off-line, data is fed to train machine learning model. If pre-trained model is available, model can be implemented in vehicle for testing in real-time. Yet, training is an exhaustive process, which requires time to collect data and to train the model. These are challenges involved in implementation.

Machine learning is crucially involved in problems such as driver's stress detection, as the detector being a machine learning system. Yet, little was studied on applying machine learning on the driver modeling in the context of ADAS. Therefore, we assert that further study on machine learning is required in the context of ADAS. We believe that research direction should consider overcoming the challenges coming from implementation. We develop a robust machine learning method that only requires a single signal. This methodology is robust due to milder requirement in quality of the signal. And our methodology use advanced machine learning technic which expand to feature extraction also.

Here, we formulate two research questions:

- Can machine learning algorithm differentiate between various kinds of situations in the context of ADAS?
- Can machine learning algorithm perform robustly with lesser input data available?

And we contribute following:

- Experiment was conducted in context of simulated partially automated driving system. Classifier is tested in three different modes of label settings.
- Novel feature extraction framework is proposed which only exploits R-R interval measurement.

1.4. Organization

This thesis onward will be composed as following. Chapter 2 covers the preliminary domain knowledge required prior to this work. It explains how physiological signal was used in this problem's context. And it states challenges in assessing psychological model, including approach by machine learning as well. The scope of this work is stated as well. In chapter 3, we show our experiment data collection procedure and preliminary analysis results. Previously, little work was done in applying machine learning to model driver's workload or distraction in the context of ADAS. In this work, we show that this approach is feasible. In chapter 4, we see that researchers neglected the challenges that will occur when their machine learning system is implemented in real world situation. So we propose new feature extraction methodology, which uses only single signal that doesn't require sophisticated signal processing prior to learning model. We only use intervals between R peaks (which can be easily measured) and exploit manifold learning to obtain more robust feature. And the result shows that our features performed better in classification than conventional features. Lastly, chapter 5 concludes our thesis with discussion.

2. Background

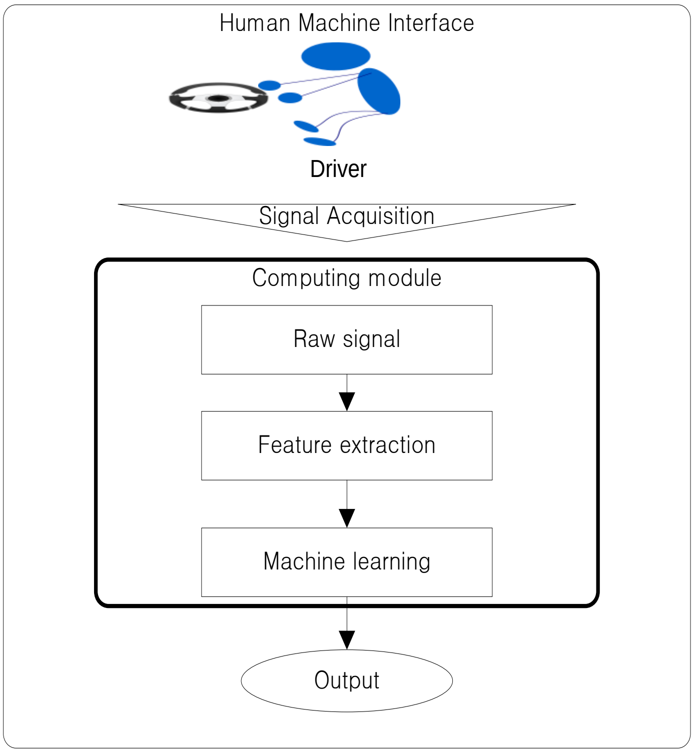

Figure 1. Formulation of general procedure in driver's state recognition. The procedure can generally be divided into four steps: 1) Signal acquisition; 2) Pre-processing; 3) Feature extraction; 4) Machine learning.

In this chapter, we present the prerequisite for driver's state detection problem. Figure 1 explains general framework in driver's state detection, which is also same to the framework used in other problems such as affect recognition[10]. In the following subsection 2.1, we present the literature survey on this framework. We present the advantage and reason of choosing physiological signal for input data. In subsection 2.2 we discuss specific methods that has been used in other literatures, which focuses on application of machine learning algorithms, including feature extractions. In subsection 2.3, we summarize and discuss the disadvantage in the framework.

2.1. Physiological signal

Various data sources have been used in human's behavior or psychological state detection, especially physiological signals[10]. In the context of driving, videos and CAN (Controller Area Network) bus data were also used[11], [12]. This work focused on the physiological signal, considering that physiological signals can be perceived as a direct measure of response. The use cases of physiological signals used for psychological state recognition are introduced in Table 1. The types of measurements available are ECG (electrocardiogram), EEG (electroencephalography), EOG (electro-oculography), EMG (electromyography), BVP (blood volume pressure), PPG (photoplethysmography), GSR (galvanic skin response), resp (respiration) and eye-gaze data. Eye-gaze data are commonly used for distraction along with video signals. For the rest of physiological signals were all common for emotion-related models. ECG is known to be the most cost-efficient, yet rich, among other physiological signals[7]. Heart rate (HR) and heart rate variability (HRV) are key features that can be extracted from ECG. HR and HRV can also be extracted from other signals such as PPG and BVP. Yet ECG is considered to be most accurate in HR and HRV extraction. We can safely conclude from this survey that HR and HRV are most crucial features required in psychological state detection. The details of the survey can be found in Table 1 & 2.

In this study, especially ECG was utilized. We intended to implement the methods in vehicle with minimum cost, so chose only one signal. ECG is known to be relatively cheap among physiological measurement, yet rich in information[7]. Video data is considered to be cheaper, but it has a disadvantage, that it is possible for the human subject to hide (or pretend) its psychological state[13]. Video measurement turns out to be not robust to illumination change, which some researchers have studied to solve it[11]. Yet, for real application, we concluded that this risk is not desirable. For CAN bus data, as it is considered to be an indirect measurement of the driver[14], it was excluded as well.

Table 1. Physiological signals used in previous work

Authors	Year	Physiological measurements	Target
Nasoz, Fatma et al[15].	2010	GSR, skin-temperature, ECG	emotion
Healey, Jennifer A et al[6].	2005	EKG, EMG, EDA, Resp	stress
Rigas, George et al[16].	2012	ECG, EDA, Resp	stress event
Katsis, C et al[17].	2008	ECG, EMG, Resp, EDA	emotion
Jeong, In Cheol et al[18].	2007	ECG	stress
R. R. Singh et al[19].	2012	GSR, PPG	stress
Mehler, Bruce et al[20].	2009	SC, HR, Resp, EMG	stress
Healey, J et al[21].	2000	EKG, GSR, resp, EMG	stress
Martinez, Hector P et al[22].	2013	SC, BVP	emotion
Healey, Jennifer et al[23].	1999	BVP, EMG, Resp, GSR, EKG	stress
Liu, Tianchi et al[24].	2015	Eye	distraction
Liu, Tianchi et al[25].	2016	Eye	distraction
Zhang, Jianhua et al[26].	2015	EEG, ECG, EOG	workload
Lee, Dae Seok et al[27].	2016	PPG	Stress
Solovey, Erin et al[9].	2014	SC, ECG	workload
Wang, Jeen Shing et al[28].	2013	ECG	Stress
Yang, G et al[29].	2009	ECG	workload

2.2. Machine learning

It is naturally accepted that psychological states have certain relationship with physiological responses. For example, heart rate increases when stress increases. Yet, this mapping is not explicitly known. To overcome this gap, researchers often exploited machine learning algorithms. The algorithm’s role is to model the psychological states as a function of physiological responses. So with any metrics (ex: HR) that reflects psychological response, one can use those metrics as feature and then feed into machine learning algorithms. In most of the cases, these metrics were adopted from clinical domains.

Table 2. Heart-related features used in previous works

Authors	Signals used	Feature names
Nasoz, Fatma et al[15].	GSR, skin-temperature, ECG	Min, Max, Mean, Std of HR
Healey, Jennifer A et al[6].	EKG, EMG, EDA, resp	HR, LF/HF
Rigas, George et al[16].	ECG, EDA, Resp, CAN	HR, HRV, AR coefficient
Katsis, C et al[17].	ECG, EMG, Resp, EDA	Mean amplitude of peak, HR, Mean absolute first order difference of intervals
Jeong, In Cheol et al[18].	ECG	HF, LF, VLF
R. R. Singh et al[19].	GSR, PPG	Pulse height, Pulse rise time, Pulse fall time, PPG cardiac period, Instantaneous HR, HF, LF, VLF, Total power, LF/HF, PPG respiration, HR(mean, sdnn rmssd, pnn20, pnn50)
Mehler, Bruce et al[20].	SC, HR, Resp, EMG	R-R interval
Zhang, Jianhua et al[26].	EEG, ECG, EOG	HR, HRV
Lee, Dae Seok et al[27].	PPG	AVG_PR, STD_PR, VAR_PR, PSD_LF, PSD_HF, PSD_LFHF
Solovey, Erin et al[9].	SC, EKG, CAN	Mean, Std, Min, Max of HR
Wang, Jeen Shing et al[28].	ECG	HRV: SDNN, RMSSD, NN50, pNN50, VLF, LF, HF, LF/HF
Yang, G et al[29].	ECG	8 coefficients of frequency component from wavelet transform

2.3. Summary

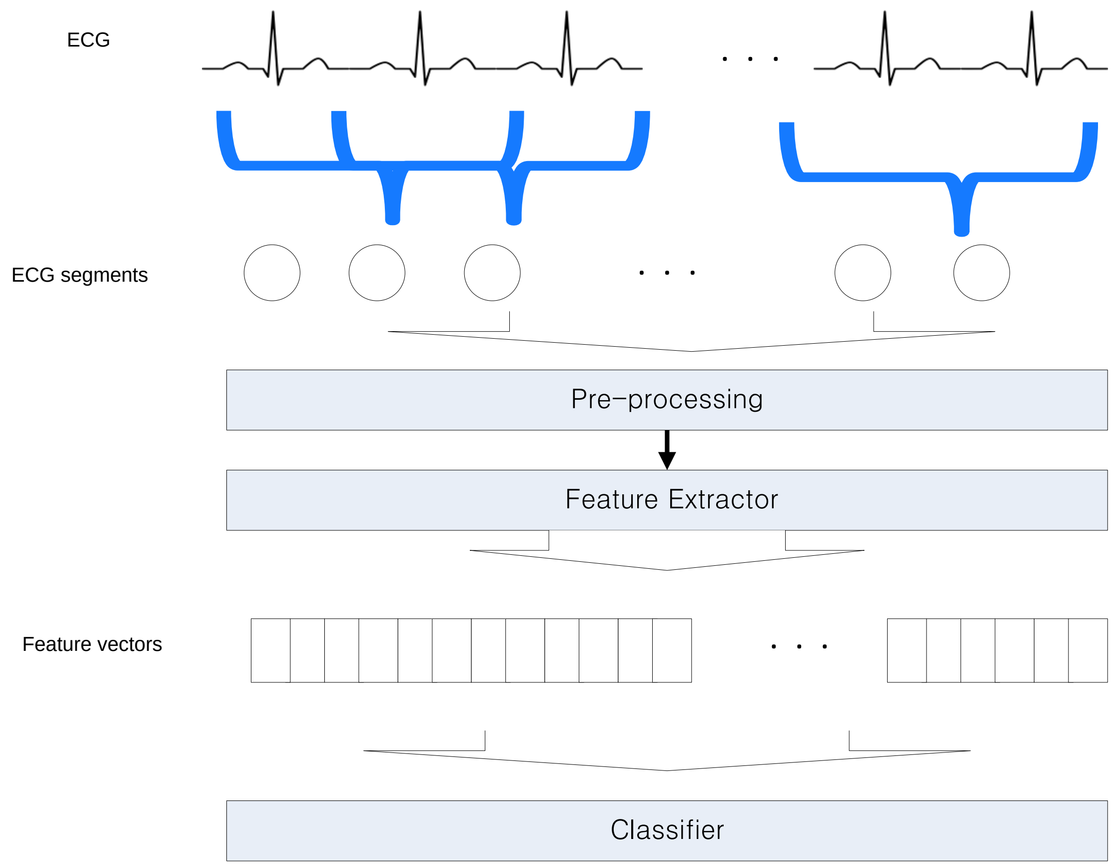

Figure 2. General framework is derived after literature survey.

Various methods that were used in previous works can be generalized by a framework as depicted in Figure 2. This framework can be divided into several steps. First, sliding window is applied to ECG signal. After that, each segments are processed to compute features, such as HR. As one feature metric is not enough, one has to extract many metrics from same signal. In other words, each features are just different representation about same data.

And in this framework, signals are mapped into a feature space. The learning model learns the target function from spatial information of data points in feature space. But the time information is not conveyed in feature space dimension. In this feature space, each data point might have time-dependencies which is not manifested through spatial information such as Euclidean distance between sample points. While previous works use multiple sensors to get enough information, we can use single sensor data with different data processing method that extracts time-dependent information.

3. Partly Automated Driving Simulator Experiment

3.1. Data collection

While Adaptive Cruise Control (ACC) system keep the vehicle in the lane, drivers might get distracted by other in-vehicle tasks or start to pay less attention to the road. This raises a safety concern and reveals the need for monitoring driver's state, especially those that can be adverse for safe driving. Driver's behavior, while driving a vehicle with such functions, was vastly studied and analyzed. However, little attempts were made to apply machine learning algorithm to automatically assess driver's situation[3]. Therefore, we have conducted an experiment to collect physiological sensor data to test proposed machine learning module to estimate workload.

In this study, we generally aim to observe the situation where drivers using ACC are distracted from various causes. When drivers are engaged in other tasks, the driver will be overloaded. Physiological sensors are expected to reveal the response from workload changes. Many types of research have tried to observe these sensor data, yet less studied on how to utilize such data.

All the experiments were performed, on a driving simulator software, City Car Driving (http://citycardriving.com/). The ACC was simulated by well-designed static video, which cover critical events: pedestrian crossing, approaching traffic light and ramps on and off highways. During this experiment, subjects were asked to press "Take Over" button on the steering wheel as soon as they identify a critical event. Critical events were: when vehicle meets red traffic light, pedestrian crossing or other vehicles entering into the driver's lane. Drivers' self-reported workload levels were collected vocally during experiment.

The experiment was largely consisted of successive three driving sessions. Driving scenario for each session was: 1) driving urban road with secondary tasks; 2) driving on the highway with secondary tasks; and 3) in highway without secondary tasks, which stimulate the low workload state. There were two types of secondary task: visual intensive and mental intensive, with fixed intervals (1 minute). In the experiment, 3 kinds of each type, total 6 kinds of the secondary tasks were adopted. Visual tasks included making a phone call, typing in an address of a place in GPS, and 1-back task[30] with response to touch panel. Mental tasks included storytelling, arithmetic calculation, and 2-back task[30] with an oral response. All secondary tasks occurred alternatively with rest period (or baseline).

Figure 3. Hardware components for a driving simulator.

Figure 4. GE B20 Patient Monitor was used for the experiment.

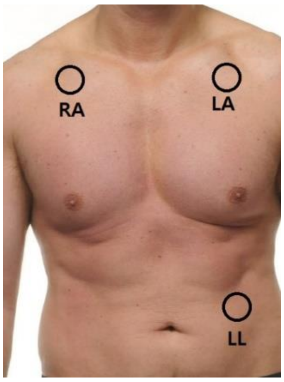

Figure 5. Electrode placement for 3 lead ECG monitoring. This configuration is more robust to artefacts from moving body.

15 subjects were recruited in this study. A valid Singaporean driving license was required. They were between 20-65 years of age and must have had at least one year of driving experience at the time of the study. The subjects should not have been suffering from any previously diagnosed cardiac or respiratory disorders. No other selection criterion was set for the recruitment of participants. Each volunteer was informed in detail about the study and their consent was obtained prior to data collection.

The experiment was conducted with Logitech G27 (Figure 3) as hardware component. Also equipped with Logitech HD Pro Webcam C920 to capture the driver's face with a resolution of 1280*720 and frame rate of 30 fps. And GE B20 Patient Monitor was used with 3 electrodes for ECG measurement (Figure 4, 5).

When each subject came, they were asked to fill questionnaire and then were informed of the introduction of the experiment. And then subjects were asked to do some practice of doing take-over and secondary tasks. Next, subjects attached electrodes and sat inside simulator and then simulation software and devices were set up. When the setup is finished, experiment and recording started. First, short instructional video for the corresponding driving session was played and simulation (static video) was played right after. First session was urban with secondary tasks and it took 30 minutes. After first session ended, instruction video for second session was played for 30 second and highway with secondary tasks simulation started. In the last session, a highway without secondary tasks started with instruction video first. Each experiment took between 1.5 ~ 2 hours. After all the sessions were complete, the experimenter asked for feedback and SGD30 was given to the subjects as rewards. And in the analysis, only 12 subjects were chosen due to measurement faults.

3.2. Preliminary analysis

Raw signal of ECG was first normalized: subtracted by the mean value of measurement then divided by standard deviation. Then sliding window of various sizes 5s, 10s, 30s, 60s, 100s, was applied. For each window, low-pass and high-pass filters were applied to remove baseline drift and Kaiser filter[31] was applied before Fourier Transform. The features were extracted from each window. Seven basic features, HR, RRV, PTotal, LF, HF, LF/HF, R peak magnitude (RPM) were extracted. Each feature was computed as follows:

Table 3. List of features used

Names	Description
HR	$\mathrm{HR} = \frac{60}{mean(R - R\ intervals)}$
RRV	RRV = $\frac{std(R-R\ intervals)}{mean(R-R\ intervals)}$
PTotal	Sum of components in FT of R-R intervals, which has frequency higher than 0.4
LF	Sum of components in FT of R-R intervals, which has frequency between 0.04 to 0.15
HF	Sum of components in FT of R-R intervals, which has frequency between 0.15 to 0.4
LF/HF	Ratio from LF to HF
RPM	mean of R peak magnitude

Feature vectors were normalized using Z-score to unify the scale. Next, features were fed into Extreme Learning Machine[32], single layer with regularizing factor C. Three types of analysis was conducted. For each, different modes of labels were defined. Through analysis, we prove that there are identifiable differences in terms of physiological changes between different types of situations.

3.3. Result

Three different analysis was done on our collected data. We used different class labels for each analysis to verify that ECG signal can reveal different patterns between various situations. All analysis were done subject dependently. Accuracy was computed as ratio of correctly predicted labels to sample size.

First analysis was performed only on 3rd driving session. In 3rd session of driving, we set traffic density to be dense in first half and zero (no other vehicle on road) in second half. Intention was to invoke boredom to driver. We show that in the context of partly automated driving, boredom of the driver can be detected. But through comparison from various comparison for different window sizes, it shows that longest size is most accurate (Figure 6). This conforms the fact from the survey[4] that in long term observation, heart rate in first 30 minutes and second 30 minutes reveals significantly different mean.

Second analysis used all three driving sessions. As Healey’s experiment suggests, driving in urban areas and highway imposes different stress levels. So we labelled each driving session different label and trained classifier. With ECG signal only, it also showed that classifier can differentiate different levels of workload (or stress) due to driving environment. Yet, sufficiently long enough window size is necessary (Figure 7).

In third analysis, we used subjective workload ratings as label. We labelled 1 ~2 is low and 3 is medium and 4~5 is high. Result also shows that training classifier out of ECG signal is feasible. Yet this still isn’t free from requirement of sufficiently long window size (Figure 8).

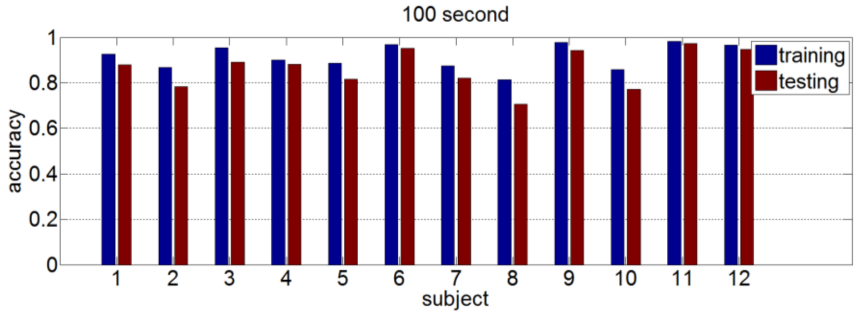

Figure 6. Classification accuracy, when classifying normal to under-loaded workload.

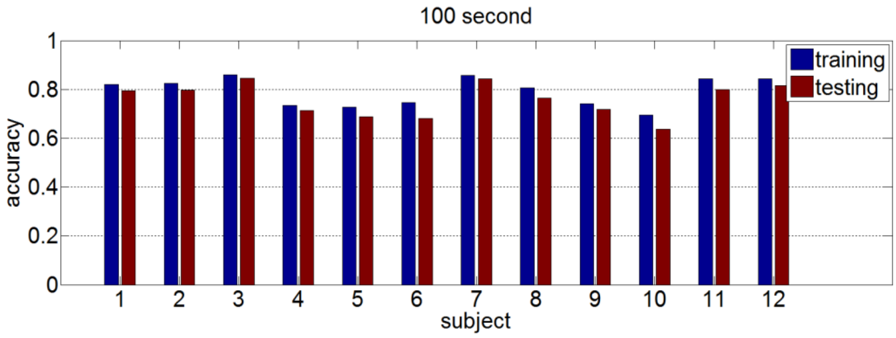

Figure 7. Classification accuracy, when classifying between different driving scenarios. Each scenario was labelled as high, medium and low workload.

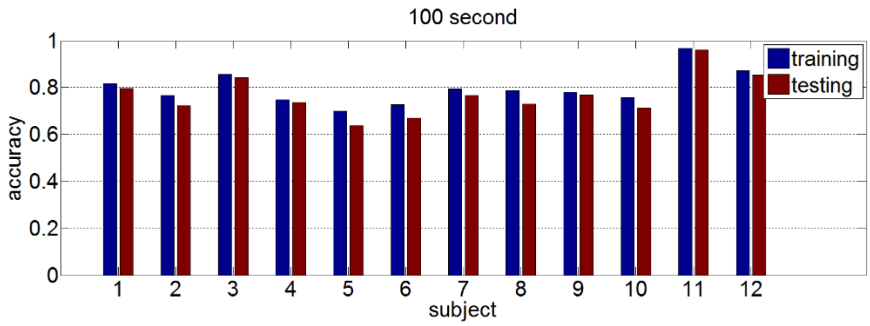

Figure 8. Classification accuracy, when classifying between high, medium and low workload based on subjective ratings.

One disadvantage that comes from large window is that it becomes less appropriate for instantaneous detection. For first and second analysis, boredom or different workload level due to driving environment is long term change, not abrupt change of state. But for ADAS, it is important to enable the system to capture instantaneous changes. Yet, in third analysis, while secondary tasks takes no longer than one minute, system only get 8 out of 10 right using 100 second window.

3.4. Summary

In this chapter we devised experiment and data collection. We intend to verify that even if drivers are driving with aid from ADAS, they can suffer from inadequate level of workload. And its workload level is likewise detectable with machine learning system. Also we show that with only ECG signal, although while some data resolution issue (ex: window size) are present, is sufficient for workload detection.

4. ECG Feature Extraction from R-R interval with Unsupervised Extreme Learning Machine

4.1. Introduction

Machine learning has been applied to various areas, such as emotion recognition and stress detection [6], [33]. In this context, the machine learning system gets input data from sensors attached to a human subject. Specifically, this can be implemented to vehicle driver so that system adapts according to driver's situation to assist driving. There were many endeavors to computationally learn driver’s human factor for the sake of driving safety. The endeavor for those human factors focused on learning from physiological signals. The challenge here comes from the complexity of physiological signals and complexity of human factor itself[8], [23]. In this work, we propose robust methodology that extract features from only one simple measurement, the interval between heart beats. Naïve and standard solution to this problem is to collect various signals from many subjects. But collecting data from multiple sensors is costly and not suitable as the device might hinder driver’s movement. In this work, we choose to use only intervals between R peaks as input data. As there are lots of cheap equipment that can measure the interval between beats, our methodology gains convenience in implementation. And we exploit manifold learning methodology to extract more information from one measurement, to compensate the loss from reducing data sources. So we developed new methods to extract feature and learn models accordingly.

Applying sliding window to extract signal’s feature is a commonly accepted method. Also those features originate from clinical studies, thus extensively studied. It has already been known by common sense that it relates well to emotions, stress and etc. But as there being no fixed mapping, machine learning algorithms are used to learn the mapping. Using feature selection or developing more sophisticated model was continuously done by many researchers[13], [33]–[39]. In phenomenal work of [6], done in the early stage of development in the research area, physiological signals and their conventional features proved that they can discriminate different stress level in 97% accuracy. And also continuous metric of stress was proposed and its correlation to features was analyzed. The result revealed that there are some features that are highly correlated, including heart rate. To learn regression model with continuous metrics is challenging as it is mentioned in [10]. And [36], [37] have adopted regression models in their work. Yet, all these variants belong to the same group, which uses conventional methods. This group typically uses clinical features and their methods are still adopted recently[40], [41]. These approaches tend to require more data and more types of measurements. We believe that it is beneficial to study on an alternative which could be more cost efficient, by enhancing machine learning capability to harness more information from same signal.

Some researchers focused in extracting information from the structure of data itself. They exploited clustering or self-organizing map, which are unsupervised learning[19]. This was more attractive as there is no need of obtaining label before training. Some reached further into nonlinear dimension reduction method, such as manifold learning[24], [25], [42]. They tried to learn complicated structure in feature space. And in [42], they concluded that the manifold itself could represent human factor index or label.

In this work, we show that from just one simple raw measurement, R-R interval, learning complex structure of the signal can derive discriminative feature of workload. In traditional methods, researchers rely on clinical prior knowledge. They apply domain knowledge, i.e., what are the physiological response from stress or workload and how are they measured. And they compute that measurement, which is high dimensional features extracted from the single signal. And machine learning component will then be trained from those features. So in our methodology, we extend the machine learning's role to not only do classification but to extract features as well. And also we propose a new framework of feature vector construction. As the traditional methods require signal processing technic to remove noise, the researcher needs to take care of the signal's quality as well. But our methodology only takes R-R interval as input. This measurement can be measured easily with cheap commercial equipment. Therefore our methodology is more beneficial for a real application.

4.2. Novel Feature Extracting Framework

Instead of computing numerous feature index, we only exploit R-R interval. R-R interval relieves burden of pre-processing to assure signal quality, which makes this framework preferable for real application. Many works endeavoured more on mapping to feature space, which is after signal's transformation or feature extraction. Instead, we propose novel feature which is derived from dynamic system based model of R-R interval. We tried to emphasize the time series' dynamic behaviour, such as error from prediction. We expected that actual observation on how the signal's behaviour changes is the phenomena from mental workload. After feature extraction, manifold learning plays its role to harness the hidden information that stems out of complex data structure. After learning embedding, sliding window is applied, then it's fed into classifier. Figure 9 depicts the general procedure of proposed framework. Processing ECG to R-R interval is out of our scope. Commercially available equipment, such as fitness tracker or smart watch can provide solution. Here, we focus on how to process and learn workload model out of R-R interval time series. As any hardware can solve this pre-processing, our method can become robust to signal quality and more efficient in implementation.

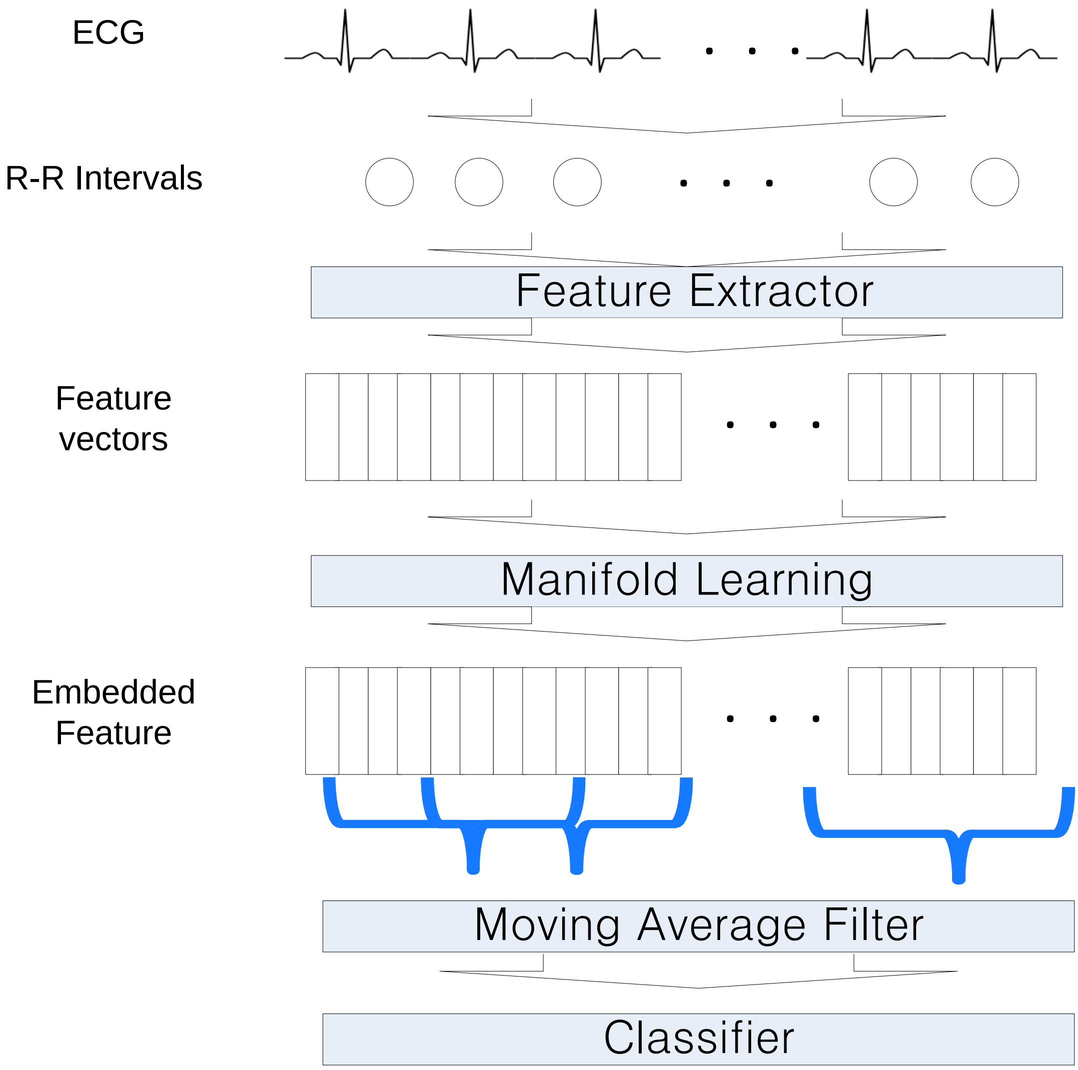

Figure 9. Scheme of proposed framework for feature extraction

4.2.1. Time lag embedding

In nonlinear dynamic analysis, time lag embedding is commonly used method. We will use time lag embedding along with our proposed feature for comparison to verify that our novel feature is feasible solution to reveal dynamics from time series. According to Taken's embedding theorem[43], just from one-dimensional time series we can construct multi-dimensional phase space which has the same topology. In other words, it can reveal the dynamics of the system. Delay embedding can be done as the following:

$$\vec{x}_i = \left[u_i, u_{i+\tau}, \dots, u_{i+(m-1)\tau}\right]^T. \tag{1}$$

After phase reconstruction, recurrence plot is commonly used to inspect its behavior[44], [45]. This methodology starts from computing recurrence matrix from reconstructed phase space as follows:

$$R_{i,j} = \Theta\left(\varepsilon_i - \left\|\vec{x}_i - \vec{x}_j\right\|\right). \tag{2}$$

As R-R interval is nonlinear systems, it is rational approach to apply nonlinear dynamic methods to identify the dynamic behavior of R-R interval. Also to use it as features[44]. This also shares the same approach as our proposed features, as it tries to use changes happening in R-R interval time series as the input of machine learning algorithms.

4.2.2. R-R interval dynamic based feature

In application, it is likely that only one signal to be given to machine learning system. So we focused on some simple raw signal, R-R interval. R-R interval is a key ingredient in ECG feature extraction. Moreover, as it is a crucial cardiovascular measure, a similar index from PPG or BVP can be obtained as well. So we propose an algorithm that analyses R-R interval. As commercial equipment like smart watch or fitness tracker can track heartbeat, we believe this will be surely beneficial for application in future.

Heart is not a simple oscillator with a fixed frequency, it is not simple to predict the timing of next beat. But still, one can try to build a simple model to predict and also record its error. As traditional HRV related features are all about measuring those irregularities, we assume that collecting time series of the mentioned errors from prediction carries the same information as those traditional feature vectors. From this idea, we developed our new features for this problem.

First, we present the model for R-R interval prediction. We denote t_i for the time point where an R peak occurs. The subscript 'i' denotes its index, so occurrence time for next R peak will be denoted as t_{i+1}. $\mathrm{r}(t_i)$ will denote interval between the peak of '$\mathrm{i}-1$' and 'i'. We will develop an approximation function from Taylor's series using up to first order term, which is a function that predicts next R-R interval:

$$\mathrm{r}(t_{i+i}) = \mathrm{r}(t_i) + \frac{r'(t_i)}{1!}(t_{i+1} - t_i) + \varepsilon. \quad (3)$$

On the right-hand term $(t_{i+1} - t_i)$ can be substituted as $\mathrm{r}(t_{i+i})$ from its definition. And by trimming out the higher order terms as error term, we can get the following forward prediction model of R-R interval time series:

$$\hat{r}(t_{i+1}) = \frac{r(t_i)}{1-r'(t_i)}. \quad (4)$$

The model takes the form of a first order autonomous system or a stationary system. From the theorem in, [46], we know that this model can only either monotonically decrease or increase. We segment R-R interval time series, in which each segment's first order difference will all have the same sign. In other words, we fit R-R interval time series as a piecewise stationary system using the formula (4). As $r'(t_i)$ is unknown, we compute it from numerical differential methods. As $\mathrm{r}(t_i)$ is unequally sampled, we compute Lagrange

Interpolation to imitate the function and take its derivative. Next our proposed feature vector is constructed as following:

$$\boldsymbol{X}_i = [\mathrm{r}(t_i), \quad r'(t_i),\ \hat{r}(t_i) - \mathrm{r}(t_i) \ \ ]^T. \tag{5}$$

Therefore we expect this feature vector will represent some changes take place in R-R interval time series. We assume that machine learning algorithm can differentiate whether this change is natural or comes from external factors (such as stress or workload).

4.2.3. Unsupervised Extreme Learning Machine (US-ELM)

Extreme Learning Machine is a generalized machine learning framework with low computation, yet does not compromise accuracy[32]. Upon ELM, Unsupervised Extreme Learning Machine[47] stems out as a solution for manifold learning. US-ELM follows manifold regularization framework. This framework starts with an assumption that the sample points that are similar to each other will yield same prediction result[47]. Therefore we need to minimize the cost function accordingly as follows:

$$L_m = \frac{1}{2}\sum_{i,j} w_{ij} \left\| P(y|x_i) - P(y|x_j) \right\|^2. \tag{6}$$

w_{ij} Represents pair-wise similarity, or weight in the graph. The weight will be nonzero when they are close, otherwise zero. If this similarity is considered as a weight of a graph then matrix $\mathbf{W}$ becomes affinity matrix or similarity graph. From spectral clustering[48], this approach is often adopted. By using this idea, this assumption becomes as following:

$$\hat{L}_m = \frac{1}{2}\sum_{i,j} w_{ij} \left\| \hat{y}_i - \hat{y}_j \right\|^2. \tag{7}$$

Which can be denoted as:

$$\hat{\boldsymbol{L}}_m = Tr(\boldsymbol{Y}^T \boldsymbol{L} \boldsymbol{Y}). \tag{8}$$

$\boldsymbol{L}$ denotes graph of Laplacian or Laplacian matrix. Now we can take US-ELM as a manifold learning algorithm that will map input $\boldsymbol{X}$ to embedding $\boldsymbol{Y}$. According to [47], US-ELM formulation comes as follows:

$$\min_{\beta \in \mathbb{R}^{n_h \times n_o}} \|\boldsymbol{\beta}\|^2 + \lambda\, Tr(\boldsymbol{\beta}^T \boldsymbol{H}^T \boldsymbol{L} \boldsymbol{H} \boldsymbol{\beta})$$

$$s.t. \qquad (\boldsymbol{H\beta})^T \boldsymbol{H\beta} = \boldsymbol{I}_{n_o} \qquad . \tag{9}$$

Which can be solved as a generalized eigenvalue problem:

$$\left(\boldsymbol{I}_{n_h} + \lambda \boldsymbol{H}^T \boldsymbol{L} \boldsymbol{H}\right)\boldsymbol{\nu} = \gamma \boldsymbol{H}^T \boldsymbol{H} \boldsymbol{\nu}. \tag{10}$$

$\boldsymbol{H}$ refers to ELM feature mapping and $\boldsymbol{\beta}$ stands for output neuron's weight: which will be the eigenvectors from generalized eigenvalue problem. US-ELM is largely inspired by Laplacian Eigenmaps[49] and spectral clustering[48] as it shares similar motivation and characteristics. It exploits graph Laplacian, which possess many desirable characteristics that can be used to analyse the graph, which takes vertices as data samples and weights that can be distance or similarity. $\boldsymbol{L}$ is computed from $\boldsymbol{L} = \boldsymbol{D} - \boldsymbol{W}$, in which $\boldsymbol{D}$ is degree matrix of vertices and $\boldsymbol{W}$ as similarity matrix. The similarity matrix happens to be very alike to recurrence matrix used in recurrence analysis for nonlinear dynamics by definition. Therefore we also combine embedded time series as input for US-ELM and compare it with US-ELM taking our proposed feature as input.

4.2.4. Modified USELM

Here, we propose a different weight matrix $\boldsymbol{W}$ that doesn't use k Nearest Neighbourhood graph (details of nearest neighbour graph can be found in [49]). In detail, when R-R interval is segmented into piecewise stationary parts, we computed matrix $\boldsymbol{W}$ only on that part. And we diagonally concatenated matrix to form the same size to usual matrix $\boldsymbol{W}$. Other index were set to 0.

In the end, we basically cluster the feature vectors according to piecewise stationary segments. From spectral clustering algorithms paper[48], the diagonal block matrix form of $\boldsymbol{L}$ represents clusters. Therefore we enforce the graph laplacian to cluster each piece-wise stationary segments to form a cluster. We expect that clusters can capture the time dependent information from data.

4.3. Analysis

4.3.1. Data set

For the experiment, we use benchmark dataset from [1], [2]. The experiment protocol can be found in the Table 4.

Table 4. Experiment Protocol

	Stage[1]	**Duration (mm:ss)**[1]	**Labelling**
1	Sensor verification	2:00	N/A
2	Task practice	5:00	N/A
3	Habituation period	25:00	N/A
4	Drive (reference)	3:00	Normal
5	N-back test A	2:30	High
6	Drive (recovery)	3:00	Normal
7	N-back test B	2:30	High
8	Drive (recovery)	3:00	Normal
9	N-back test C	2:30	High
10	Drive (recovery)	3:00	Normal

The detail of experiment can be found from the referenced paper[1], [2]. In our analysis, we tried to classify normal driving period as baseline and period during N-back test as elevated workload. Therefore our analysis becomes binary classification problem.

4.3.2. Analysis

The analysis was subject dependent. For each subject, 5 types of feature extraction with two types of the classifier was tested. For classifier SVM[50] and WELM[51] was chosen. For feature extraction, first type was the traditional methods which is same to the methods used in section 3. And other four used the proposed framework: combined with modeling of R-R interval and manifold learning. Through the analysis, we verify that our alternate approach can extract meaningful features so that classifiers can easily discriminate different workload levels.

Stage 1, 2 & 3 were used as a reference signal for the preprocessing purpose. Reference signal's mean and standard deviation was computed and the whole ECG signal was subtracted by reference mean then divided by reference standard deviation. Then zero-phase low pass and high pass filter were applied and peak detection algorithm detected R peaks.

The features used in the traditional method are following:

Table 5. List of conventional features used

Feature's name	Description
HR	mean heart rate
RRV	time difference between two consecutive R waves (used to compute the heart rate variability in the time domain)
PTotal	Total power of the signal in frequency domain
LF	Low-Frequency Components, PSD from 0.04 to 0.15 Hz
HF	High-Frequency Components, PSD from 0. 0.15 to 0.4 Hz
LHR	Low and High-Frequency Ratio, LF/HF;
RPM	R Peak Magnitude

For the second type of feature extraction, we computed R-R dynamic model based feature vector, which has R-R interval index and its derivative and prediction error. Moving average filter was applied to this feature vector and then the feature vector was fed to the classifier to train the model.

For the third type, R-R dynamic model based feature vector was embedded to 10d space using US-ELM. Laplacian matrix was computed from 5 nearest neighborhood graph. And 1000 for number hidden neurons and 0.1 for lambda was chosen as hyper parameter for US-ELM. Embedded 10d feature vector was filtered by same moving average filter with the one used in second type feature extraction. The classifier was trained after filtering feature vector.

In the fourth type of feature extraction, time lag embedding was applied on R-R interval. Then we trained US-ELM with the same setting and embedded to 10d space. Before training classifier, moving average filter was applied as well.

For the last type, we used our proposed modified US-ELM. As the weight of similarity matrix in graph Laplacian is only computed between piece-wise stationary segment, there is no need to specify k for nearest neighbor. Other than that, US-ELM and moving average filter with the same setting were applied and feature vector was fed to the classifier.

For WELM, number of hidden neurons were set to 1000 and regularization factor C was set to 1024. And for the size of the window: 5s, 10s, 30s, 60s and 100s were chosen for traditional methods. Other feature extraction also involved different window size accordingly as moving average filter was applied. In this case, as R-R interval indices are not equally sampled, we assumed that normally R-R interval is roughly sampled for each 0.75 seconds. From this setting our proposed feature extraction chose 7, 14, 39, 79 and 133 points moving average filter accordingly. All feature vector was normalized by min-max normalization method before classification as follows:

$$\mathbf{X}_{norm} = \frac{\boldsymbol{X}-\min(\boldsymbol{X})}{\max(\boldsymbol{X})-\min(\boldsymbol{X})}. \tag{11}$$

G–mean was used as evaluation matrix of classification, as the dataset has an imbalanced class ratio. G-mean stands for geometric means of accuracy per class (ratio of correct label to a number of sample in each class). Accuracy per class is equivalent to ratio from a diagonal element from column j to sum of column j in confusion matrix. For binary classification it goes as follows:

$$G - mean = \sqrt{\frac{TP}{TP+FN} \times \frac{TN}{TN+FP}}. \tag{12}$$

In our case, the elevated workload is positive case and baseline as negative. Using interpretation as the geometric mean of each ratio of the diagonal element to column sum in column j can be also extended to multiclass classification evaluation.

The analysis was performed subject dependently. For each subject, the algorithm was tested and 10 fold cross validation was exploited. For each subject, the feature vectors were divided into 10 sets and each set was put aside as a test set in turns and remaining 9 sets were used for training. For each subject, we took an average of 10 classification’s G-means for both training and testing.

4.3.3. Result

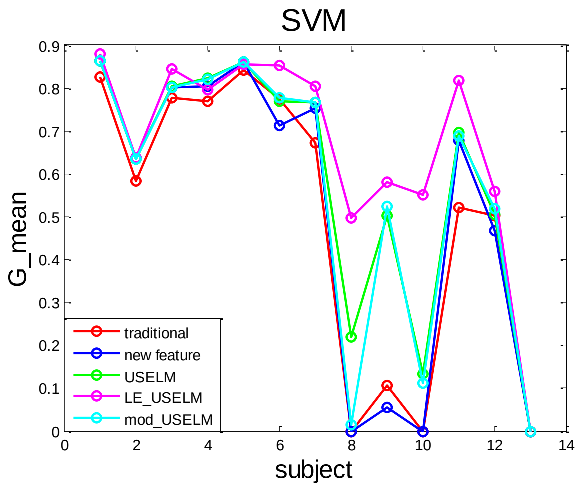

Figure 10. Results with 5 second windows using SVM

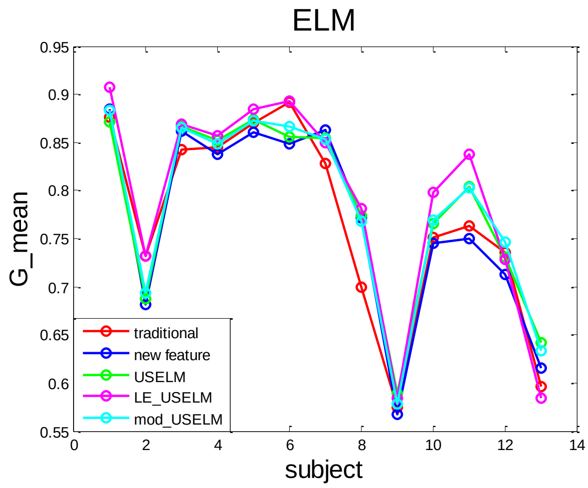

Figure 11. Results with 5 second windows using WELM

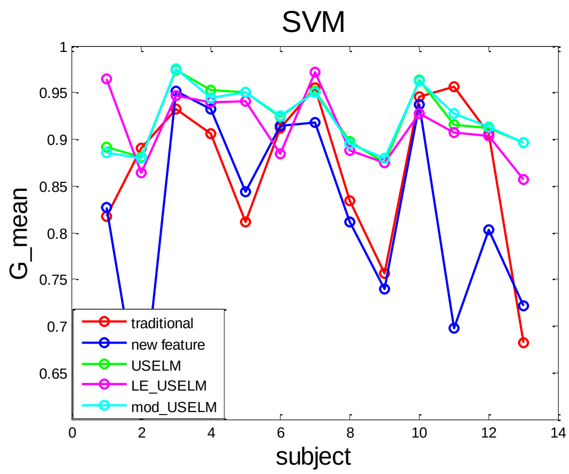

Figure 12. Results with 100 second windows using SVM

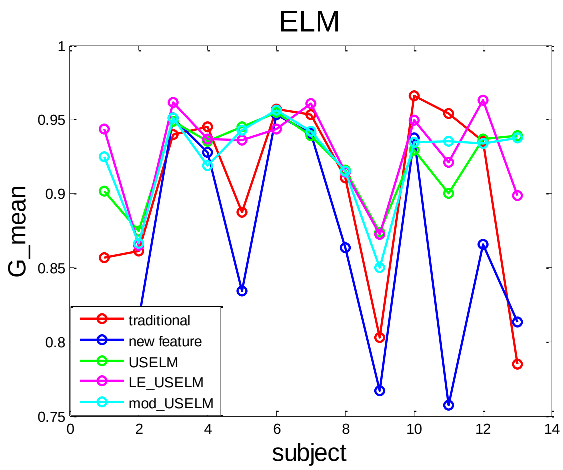

Figure 13. Results with 100 second windows using WELM

In Figure 11 ~ 14, ‘traditional’ depicts the conventional method that was also used in section 3. The blue line depicted with ‘new feature’ second type expressed in the previous section. The green line depicts third type and other lines are in according orders from the previous section. Only test results are shown in the figures.

From Figure 10 & 11 it clearly reveals that when the feature extraction, using our proposed framework outperforms the traditional features most of the time. In Figure 12 &13

difference seems to decrease. In overall, when the window size is shortened, our proposed frameworks tends to be more robust in performance than traditional features.

4.4. Summary

In this chapter we intend to show new framework of feature extraction. We thought that going through tedious process of signal processing to obtain feature is inefficient. Instead, we came up with simpler process that uses R-R interval as time series and exploiting machine learning technics to extract features. It turned out that our methods perform better or similar to those traditional methods.

Yet, our new proposed time series based features did not result sufficient compared to traditional method when it was used without manifold learning scheme. But we believe that there are hidden information hidden inside, which explains the performance after manifold learning. So it will be promising to improve this work by developing time series based manifold learning method to extract more rich features.

5. Discussion & Conclusion

In this work, we present novel feature extraction method using piece-wise stationary system modeling of R-R interval with US-ELM. Our methods assume that R-R interval has irregularity from nature and it conveys import clue about human's workload. As the complicated pattern is hidden inside the time series we exploit manifold learning scheme to represent its data space in higher dimensional space.

The analysis was done subject dependently, while many works using traditional methods have done analysis subject independently. From the analysis, we observed that classification's performance can be very sensitive to many factors, for example, choice of normalization methods. As the dataset is easy to become imbalanced, performance was also easily degraded and made it difficult to validate because of small numbers of the instance for some classes. Therefore, we expect that when the quality of collected data and extracted features are reliable, analyzing across subjects can actually increase sample numbers. In results, this contributes to generalizability, makes classifier robust. And as the feature's physical meaning is well known and has a clear unit of measure, aggregation of the feature vector is very straight forward. Yet, our methodology analyzes the structure of the data points inside one subject. Therefore we can't assure the embedding for each subject will be equivalent. So we couldn't directly mix feature vectors from different subjects to do classification.

This method also has an advantage in cost efficiency. It is normal to include more measurement and features to enhance accuracy, yet costly. For a real-world application, cost-efficiency must be accounted and it is more desirable to have less measurement so the less sensors can lead to less discomfort in driving. And in this work, only R-R interval is needed. R-R interval does not strictly require precise ECG measurement. Moreover, there are many cheap commercial equipment that can collect beat to beat interval signals, including smart watch or fitness tracker. So we believe that this method is more beneficial in future development for driver assistant system that is aware of driver's states.

The potential development can be done from manifold learning domain. This work proves that it is not clinical measures such as heartrate that is effective for workload detection. We believe that algorithm that can capture the change in dynamics or R peak rhythm is most promising solution. In future, we intend to extend our methods so that we capture the driving force that is hidden behind R-R interval time series. We believe that this will result in similar direction mentioned in section 4.4, time series based manifold learning algorithm.

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