IEEE Transactions on Cognitive and Developmental Systems

Regression Based Continuous Driving Fatigue Estimation: Towards Practical Implementation

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Abstract— **Mental fatigue in drivers is one of the leading causes that give rise to traffic accidents. Electroencephalography (EEG) based driving fatigue studies showed promising performance in fatigue monitoring. However, complex methodologies are not suitable for practical implementation. In our simulation based setup that retained the constraints of real driving, we took a step closer to fatigue estimation in a practical scenario. We adopted a pre-processing pipeline with low computational complexity, which can be easily and practically implemented in real-time. Moreover, regression-based continuous fatigue estimation was achieved using power spectral features in conjunction with time as the fatigue label. We sought to compare three regression models and three time windows to demonstrate their effects on the performance of fatigue estimation. Dynamic time warping was proposed as a new measure for evaluating the performance of fatigue estimation. The results derived from the validation of the proposed framework on 19 subjects showed that our proposed framework was promising towards practical implementation. Fatigue estimation by the support vector regression with radial basis function kernel and 5-second window length achieved the best performance. We also provided a comprehensive analysis on the spatial distribution of channels and frequency bands mostly contributing to fatigue estimation, which can inform the feature and channel reduction for real-time fatigue monitoring in practical driving. After reducing the number of electrodes by 75%, the proposed framework retained comparable performance in fatigue estimation. This study demonstrates the feasibility and adaptability of our proposed framework in practical implementation of mental fatigue estimation.**

Index Terms— **Driving Fatigue Estimation, Wireless Transmission, EEG, Dry Electrode, Regression, Dynamic Time Warping**

I. INTRODUCTION

MENTAL fatigue is a gradual process that occurs in the brain and leads to reduced cognitive effort, attention, performance and efficiency. Mental fatigue induced by prolonged monotonous driving has been a major contribution to traffic accidents, higher than that of alcohol or drugs [1]. In view of the large costs, both human and economic, there is a great need to detect driving fatigue effectively and design suitable protective measures to prevent accidents.

In the literature, three main approaches of fatigue estimation can be found, based on: psychometrics, video and physiological measurements. Psychometrics based approaches involve questionnaires, filled up by subjects at respective intervals based on which fatigue level is estimated [2, 3]. This type of approach is however less reliable, as it can be biased by the subjective nature of questionnaires. Video based measurements like facial expressions have also been used as a marker for mental fatigue [4]. A more reliable approach is to use neurophysiological measures such as electroencephalography (EEG) [5-7], electrocardiography (ECG) and electrooculography (EOG) [8, 9] to estimate mental fatigue. Since brain is the primary source where mental fatigue develops, studying fatigue through brain's electrophysiological signature should be more specific and contiguous to the brain processes involved, than video-based measurements (which may be only measurable when obvious behavioral changes appear), thus allowing earlier detection.

Over the past years, numerous studies of mental fatigue have been done using EEG signals, owing to their high temporal resolution. Logarithmic power spectrum for several dominant frequencies has been shown to exhibit differences between alert and fatigue states of human brain [10]. Past studies showed different frequency bands relevant to fatigue. For instance, EEG spectra in alpha and theta bands [11]; delta, theta, alpha and beta bands derived from a single channel electrode [12]; delta and theta bands [13]; alpha burst features were used in [14] and shown to be sensitive to mental fatigue. Theta band was also shown to be indicative of the effects of fatigue [15, 16]. Therefore, there is no specific frequency band exclusively relevant in mental fatigue and thus it is important to analyze the whole EEG spectrum. Apart from using EEG spectral bands,

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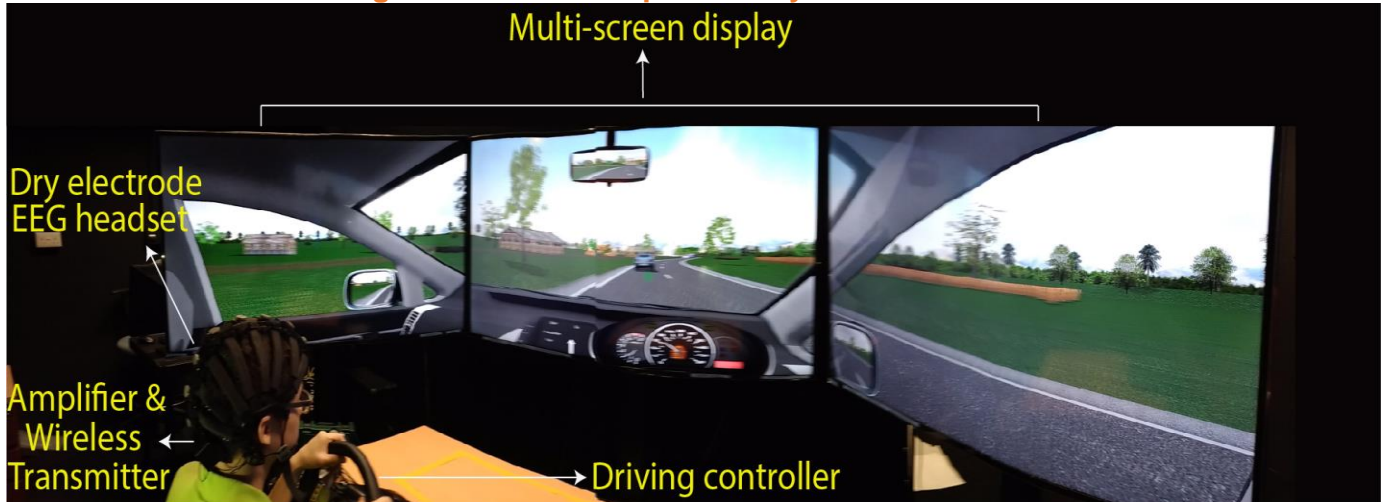**IEEE Transactions on Cognitive and Developmental Systems**

Fig. 1: Experimental setup developed to mimic real driving scenario. A multi-screen display was used to provide a wide view of sight. The setup also includes a driving controller and a wireless dry EEG recording equipment.

connectivity measures have also been applied to identify the changes from alert state to fatigued state in brain connections [17-19].

Mental fatigue has been classified into two [20, 21] or multiple [1, 12] fatigue states continuously estimated throughout the period spanning from alertness to fatigue. However, the methodologies used in these approaches have certain drawbacks with respect to practical implementation. Firstly, simple classification of alert and fatigue states is not enough to take preventive measures when the driver is fatigued in real driving. Reaction time (RT) [9] to a certain assigned task has been used as a feature to predict fatigue level [22]. However, in real conditions, it is impractical and risky to let driver conduct additional specified task for collecting RT. In addition, the pre-processing and feature extraction steps involved in such analysis are complex and time consuming [23], which is not desirable for practical implementation.

In this study, continuous fatigue estimation with a feasible methodology for practically implementation is achieved for subjects performing a driving task in a simulated driving environment. We incorporate the real driving constraints in our driving simulation and adopt a simplistic framework that is more feasible towards practical implementation in real driving conditions. The pre-processing and feature extraction steps are selected with low computational complexity for fast fatigue detection. The performance of the proposed framework is evaluated using Dynamic Time Warping (DTW) distance which is robust to small differences between the measured and observed fatigue level. To select an optimal window length and regression model, we conduct a comparative study for different time window lengths used for signals analysis, as well as various regression models. Further, fatigue estimation performance with reduced number of electrodes is evaluated in order to facilitate the practical implementation.

The paper is organized as follows. Section II discusses the methodology followed by Section III, where the results are given. The discussion is provided in Section IV. Finally, conclusion is drawn in Section V.

II. METHODOLOGY

A. Experimental Protocol

In this study, 22 healthy participants (12 males and 10 females; age: 23 ± 2.7 years, mean $\pm$ standard deviation) were recruited through advertising on the campus of the National University of Singapore (NUS). Approval for the experiment protocol was obtained from the Institutional Review Board (IRB) of NUS and written consent forms were obtained from all the subjects. The driving simulator consists of 3 large LCD screens and the Logitech G27 Racing Wheel (driving wheel, pedals and gear box). City Car Driving 1.5 was employed to virtualize cars and roads, forming a simulated country side scenario [24, 25]. The multi-screen display provided a wide view matching to the field of sight of a human eye. Subjects were instructed to continuously drive the controlled car for 90 mins [24]. The experiment comprised 2 sessions, where in each session, the subjects were instructed to follow a guiding car and brake whenever the tail red lights of the guiding car were lit, signaling the guiding car started to brake. RT is thus defined as the time interval between the moment tail red lights are lit and the moment at which the participant applies the brake. The last five minutes of the experiment were excluded from analysis due to change of the driving mode of the simulator to free driving. The interval between the two sessions was approximately 1 week. Based on RT, subjects who did not experience fatigue, were excluded from analysis. Based on this criteria, 3 subjects were excluded and a total 19 subjects were used for analysis. All the subjects were monetarily compensated for their participation after experiment completion. Fig. 1 shows the experimental setup used in this study.

B. EEG Data Acquisition

EEG data was recorded using a Cognionics 24-channel EEG headset (Cognionics, Inc., San Diego, USA) equipped with dry electrodes. The dry electrodes comprised flex electrodes used

for haired area and dry-pad electrodes used for bare skin like forehead and mastoids. The acquired EEG data was transmitted wirelessly to a recording computer. Cognionics data acquisition software was used to measure the impedances between the scalp and the electrodes and the impedance was kept below 20 KΩ. The sampling rate of data acquisition was 250 Hz.

C. Data Pre-processing

A pre-processing pipeline that requires low computational complexity was used in this work. The acquired EEG data of each channel were centered, followed by common average reference and de-trending. The data were then band-pass filtered using a 5th order Butterworth filter at cutoff frequencies of 1Hz and 40Hz. For every epoch, the number of channels for which the extreme value of the epoch was more than the sum of the mean and 5 times the standard deviation of that epoch, was counted. If this number of channels exceeded 12 for an epoch, the epoch was discarded.

D. Feature Extraction

Power Spectral Density (PSD) was used to extract spectral features from the EEG signals using Welch's method (Hamming window and 50% overlap). The obtained spectra from the EEG data were divided into five spectral bands namely: delta (1-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz) and gamma (30-40Hz). Based on these bands, five band power features (i.e., P_δ, P_θ, P_α, P_β and P_γ) and two power ratios ($P_{(\theta+\alpha)/\beta}$ and $P_{\theta/\beta}$) [26] were extracted from each channel, resulting in a total of 168 features ((5 power bands + 2 power ratios) × 24 channels).

It is known, in general, fatigue gradually appears as time lapses during driving [20]. Hence, time can be utilized as an indicator of mental fatigue level. Based on this assumption, features were linearly correlated with time and Pearson correlation coefficient was used to identify fatigue-related features. Those features with absolute correlation coefficient larger than a certain threshold were selected. The threshold was sought from a wide range, from 0.05 to 0.5, with incremental step of 0.05 and subsequently 0.1 was determined, as the performance of fatigue estimation was maximized using that threshold.

E. Regression Analysis

Based on the selected spectral features, continuous estimation of the fatigue level was done using regression analysis. Time was used as the fatigue label for training the regression model. Based on the past literature, three regression models have been widely used: linear, quadratic and support vector regression [27-29]. These three regression models have been selected to provide a comparative study of their performance to estimate driving fatigue.

Let us consider a variable Y and n number of predictors termed as $X = (x_1(t), x_2(t)\dots x_n(t))$. In this study, the independent variable X refers to the selected spectral features after the feature selection. In case of a linear regression model, Y is defined as the dependent variable having a linear relationship with n number of independent variables. The formula is stated as:

$$Y = \beta X + \varepsilon \tag{1}$$

Where β is the linear parameter and ε is the error term. Based on the training data and labels, the β for each variable and ε are calculated and used as parameters for the regression model. The dependent variable Y refers to time (selected as the fatigue label for training the regression model).

Quadratic regression, or polynomial regression of order 2, finds the nonlinear relationship between the independent and dependent variables in the form,

$$Y(t) = \beta_1 X^2 + \beta_2 X + \varepsilon \tag{2}$$

Support Vector Regression (SVR) originates from Support Vector Machines (SVM), originally introduced by Vapnik [30]. Unlike a SVM classifier, instead of being used for binary classification, SVR aims to estimate a continuous value as output [31]. The formula is stated as

$$Y = wX + b \tag{3}$$

Where w is the weight and b is the bias. If the data is not linearly separable, slack variables (ξ) are added to the model. In the case, the predicted value y is more than a certain distance ε from the actual value, a penalty factor C is included. The error function E can be stated as

$$E = C \sum_{i=1}^{L} (\xi^+ + \xi^-) + \frac{1}{2}w^2 \tag{4}$$

Minimizing this error function involves different kernel functions. Further detailed theory of SVR can be obtained in [31]. In this paper, linear and radial basis function (RBF) kernel parameters are used for SVR. The tolerance ε, regularization term C and γ for RBF kernel were optimized for each subject using an exhaustive grid search technique.

F. Dynamic Time Warping

Dynamic Time Warping (DTW) was first introduced in [32, 33] and has found wide application in speech recognition. It is used as a measure for estimating similarities between two time signals. The data points from the two signals are flexibly aligned to find intrinsically invariant distance between them [34-36]. The cost for the optimal alignment with DTW can be calculated by considering the current distance between two data points i and j, and the minimum distance between the previous data points as formulated below:

$$Cost(i, j) = dist(i, j) + M \tag{5}$$

$$M = \min(Cost(i-1, j), Cost(i, j-1), Cost(i-1, j-1)) \tag{6}$$

In this work, we propose the use of DTW as a similarity

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measure between the estimated fatigue level obtained from the regression output and actual fatigue level considered as the RT. The lower was the DTW distance value, the greater was the similarity between the signals. Other traditional similarity
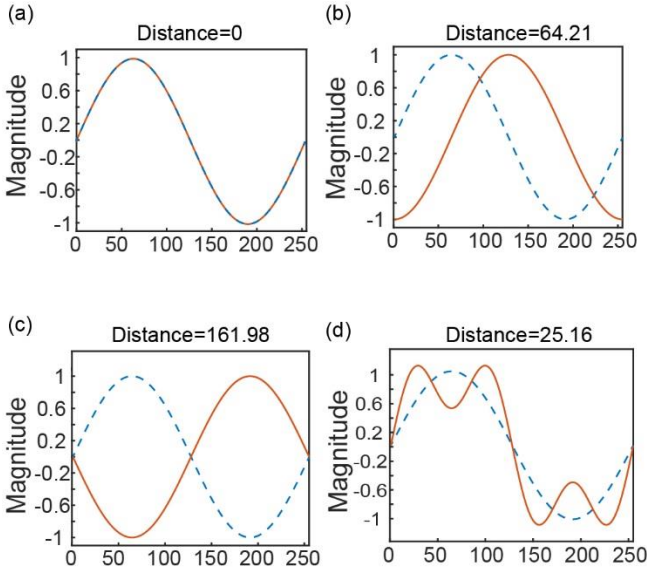

Fig. 2: Illustration of DTW distances in four simulated cases: (a) both signals are similar; (b) 90° phase shift between the signals; (c) 180° phase shift between the signals; (d) one signal consists of 3rd harmonic with the fundamental frequency and no phase difference between the signals. The orange and blue lines represent two simulated signals. DTW distance value is shown on the top of each figure.

methods, such as Euclidean distance, correlation, root mean square error, have certain drawbacks. An inflated difference is usually obtained using the traditional methods when evaluating the similarity between two signals with similar trend but slight difference in phase or minor momentary fluctuations. It should be noted that, although RT is a good indicator of mental fatigue in a driving experiment, slight differences between the estimated fatigue and the actual fatigue from RT might exist. This difference is due to the fact that EEG reflects change in mental state earlier than behavioral data like RT. Also, the temporal resolution of RT is lower than that of the EEG signals. Hence, evaluating the similarity between the estimated and actual fatigue level using the traditional methods will result in misleading conclusions for fatigue estimation. Instead of obtaining an exact value for fatigue, estimating the trend of fatigue is more crucial. DTW provides the solution to this issue. It is robust to such minor fluctuations and differences between the signals and gives a similarity measure of the trends between the actual fatigue level and estimated fatigue level. We further compared the DTW with the traditional Euclidean Distance (ED) method in the performance (see results in the supplementary materials). The results demonstrated that DTW was able to more accurately assess the extent to which two signals were similar compared to the ED. Therefore, DTW is more reliable for performance evaluation compared to the traditional methods.

It should be noted that RT cannot be easily and naturally obtained during actual driving, because even to install a device for measuring RT during real driving will pose distraction and

risk to the driver. In this study, RT was recorded for indicating the actual mental fatigue level and served as a reference for the evaluation of the proposed framework. It was not used as a feature/label to train the regression models as it was not practically available in actual driving.

We performed a simulation to demonstrate how DTW measured distance between two time series in a few typical situations, which served as a reference to interpret the results derived from real EEG data. Fig. 2 shows four cases of DTW distance measure between two sinusoidal signals. In case (a), the two signals are identical, followed by a 90° phase shift between them in (b) and 180° phase shift in (c). In case (d), the phase is kept same, but for one signal, 3rd harmonic is mixed with its fundamental frequency. It can be observed that for (a), DTW distance is 0 as the signals are identical. In (b), the two signals with slight difference in phase but with similar trends has DTW distance of 64.21. In (c), the difference between the signals is further increased and therefore, DTW distance also increases to 161.98. In (d), the signals have similar trend near zero with minor fluctuations near the peaks. DTW distance is 25.16 which is less than (b) and (c). Based on the comparisons between the four cases, it can be seen that similar curves (like (b) and (d)) with the similar trend but little differences between them still yield low values of DTW distance, retaining the trend similarity information. Higher values of DTW distance are only obtained when the trend of two signals are different from each other (as in (c)). These values give a rough baseline for comparing the results of this work.

To make the estimated and actual fatigue level comparable, following procedure was performed: a) first, a 5th order polynomial fitting was done to obtain the estimated fatigue level curve (based on the EEG power spectral features using SV regression with time as fatigue label) and the actual fatigue level curve (based on the RT data); b) the two curves were normalized to the range [0, 1]. The RT data were much sparser than EEG data in the recording. Therefore, both data were normalized in time to have identical number of data points. Finally, c) the difference between the estimated and actual fatigue level was evaluated.
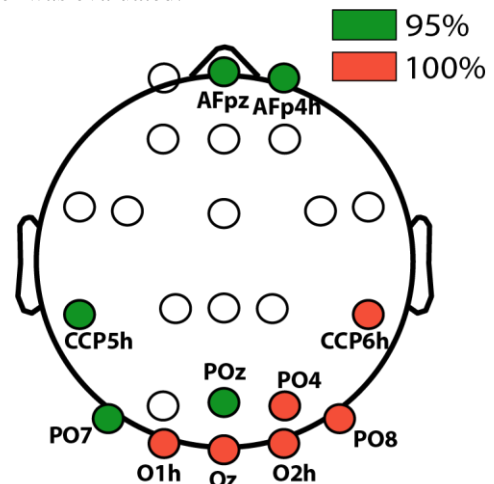

Fig. 3: Common electrodes shared after feature selection across 95% of the subjects (in green) and 100% of the subjects (in red).

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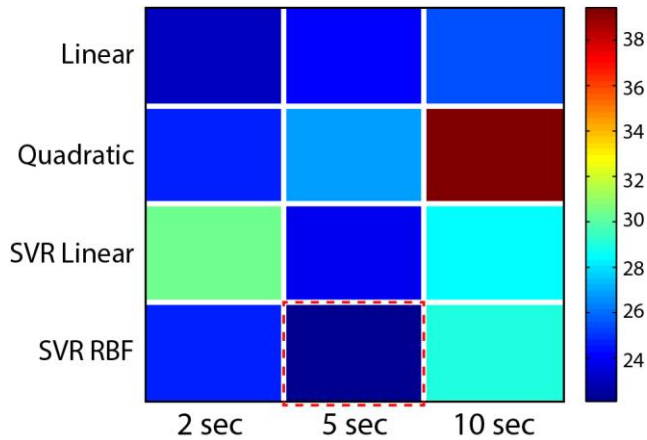
G. Evaluation

Fig. 4: Average DTW distances for all window lengths and regression models. The red dashed box indicates the best performance (obtained by using SVR model with RBF kernel and 5 sec window length).

The window length used for real-time data analysis may influence the performance of fatigue estimation. Given the practical feasibility, a short window length is desirable for timely fatigue estimation in real-time. Therefore, varying window lengths (i.e., 2 sec, 5 sec and 10 sec) were explored in this paper. The entire EEG data was segmented into epochs based on these window lengths for real-time fatigue estimation.

Another constraint in actual driving is the unavailability of data for training at the time of fatigue estimation and a pre-trained model is required. Hence, the validation of a model that is trained and tested on a single session cannot be directly generalized to practical real-time use. Therefore, the first session, recorded approximately one week before, was used for training the regression model and the trained model was then used to estimate fatigue in the subsequent driving session in this study.

III. RESULTS

Driving fatigue is estimated for all the subjects using the proposed framework. After exploring the regression models and window lengths, SVR model with RBF kernel and 5 sec window was found to give the best fatigue estimation performance (average DTW distance for all subjects=22.09). We further explored the relevant channels and the spectral bands that mostly contributed to the fatigue estimation for this 5 sec window length. The channels that contributed to fatigue estimation for 95% and 100% of the subjects are shown in Fig. 3. It can be observed that the most shared channels among participants are located in the frontal, parietal and especially in the occipital region. The frequency bands that were mostly selected during the feature selection step, corresponding to each of the common electrodes shown in Fig. 3, are listed in Table I. It can be observed that the θ/β features relatively dominantly contribute to fatigue estimation.

TABLE I
CORRESPONDING FREQUENCY BANDS OF THE COMMON ELECTRODES
SHOWN IN FIG. 3

Electrode	Frequency Bands
AFpz	θ/β
AFp4h	α
CCP5h	β
CCP6h	γ
POz	θ/β
PO4	β
PO7	γ
O1h	β
Oz	δ, α, β, θ/β
O2h	θ/β
PO8	θ/β

The mean values of the DTW distances between the actual and estimated fatigue level are shown in Fig. 4 for different regression models and window lengths. It can be observed that the variation of linear regression performance across different window lengths is negligible. On the contrary, quadratic
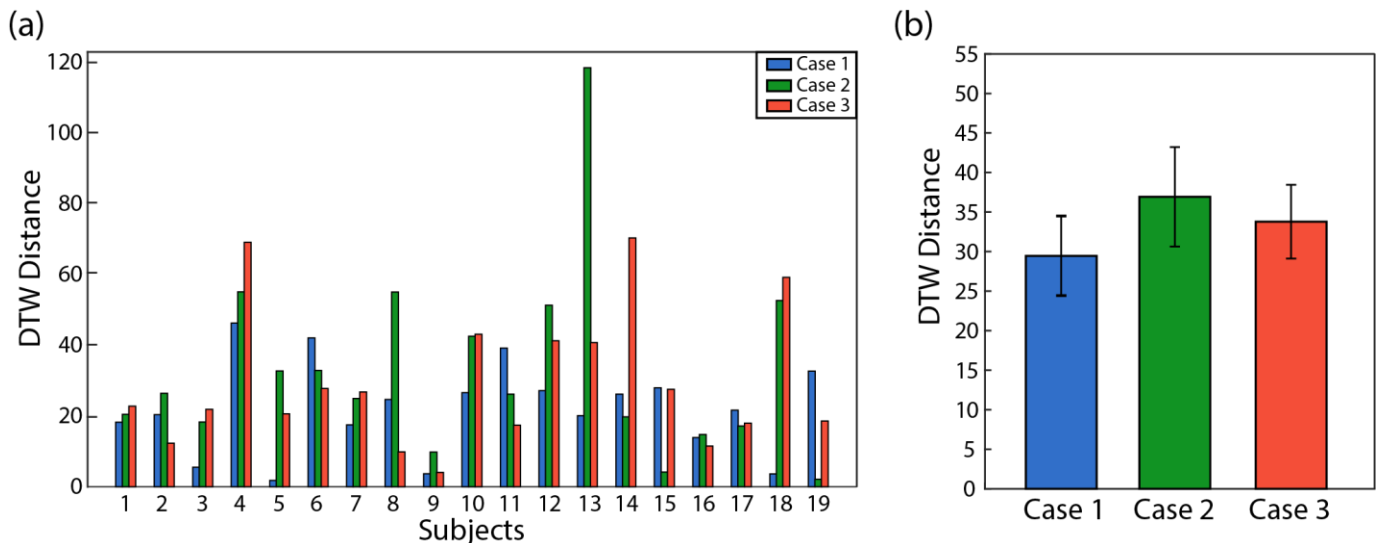

Fig. 5: The performance based on DTW distance using the SVR model with RBF kernel and 5 sec window length for three different cases. Case 1 represents the performance obtained using all the electrodes; Case 2 represents the performance obtained using the selected electrodes which are common across 95% of the subjects; and Case 3 represents the performance obtained using the electrodes which are common across 100% of the subjects. (a) Performances of individual subjects for three cases. (b) Means and standard errors of the DTW distances for three cases.

regression shows maximum variation in performance across different window lengths with a highest increase of 46.35% in the DTW distance from 5 sec window to 10 sec window. Both linear and quadratic regression show a decrease in the performance with an increase in window length. For SVR, with both linear and RBF kernel, this decreasing trend is not observed and best performance is obtained in 5 sec window. RBF kernel outperforms linear kernel for all the window lengths but the difference in performance with the linear kernel decreases with increase in the window length. The worst performance is obtained for quadratic regression using 10 sec window length (mean DTW distance= 39.44).

We evaluated the fatigue estimation performance using reduced number of electrodes to increase feasibility in practical implementation [37]. Based on results shown in Fig. 3, we selected two sets of reduced number of electrodes (electrodes common to 95% of the subjects and electrodes common to 100% of the subjects) and compared their performance with the performance obtained using all the electrodes. Therefore, three cases were analyzed: (1) performance with all the electrodes, (2) performance with electrodes common to 95% of the subjects and (3) performance with electrodes common to 100% of the subjects (Fig. 5). The performance for the three cases was evaluated using the optimal combination of SVR with RBF kernel and 5 sec window for all the subjects. One-way ANOVA results showed no significant difference between the three cases. Therefore, similar performance was obtained using reduced number of electrodes. It is worth noting that the performance under electrode reduction was better than the use of all electrodes for about 40% of the subjects (8 out of 19),

Fig. 6 shows the estimated fatigue (red line) and the actual fatigue (blue line) averaged across all the subjects using SVR with RBF kernel and 5 sec window length (only the polynomial line fit is shown for better visualization). It can be observed that the estimated fatigue level follows the trend of the actual fatigue level.

IV. DISCUSSION

The main objective of this work was to develop a fatigue monitoring framework which orients towards the practical scenario of realistic driving. Real world driving posits several constraints which demand elaborate experimental paradigms. Therefore, the experimental protocol and the fatigue estimation framework for this work were designed to facilitate their implementation in the practical situation. An EEG headset with wireless data transmission and dry electrodes was used in this work. The wireless data transmission allows mobility so as not to restrict movements of the driver. The majority of papers employed wet electrodes for EEG acquisition [13, 15, 17, 18] which has several drawbacks in terms of practical implementation in actual driving. Using wet electrodes demands additional effort to apply gel to the contact surfaces of electrodes and therefore additional preparation time is required compared to using dry electrodes. Additionally, wet electrodes are not suitable for long-term recording, as drying gel may result in poor signal quality. To overcome these

drawbacks, dry EEG electrodes were utilized in this work as it is more suitable for real-time fatigue monitoring in actual driving conditions. Pre-processing steps that require low
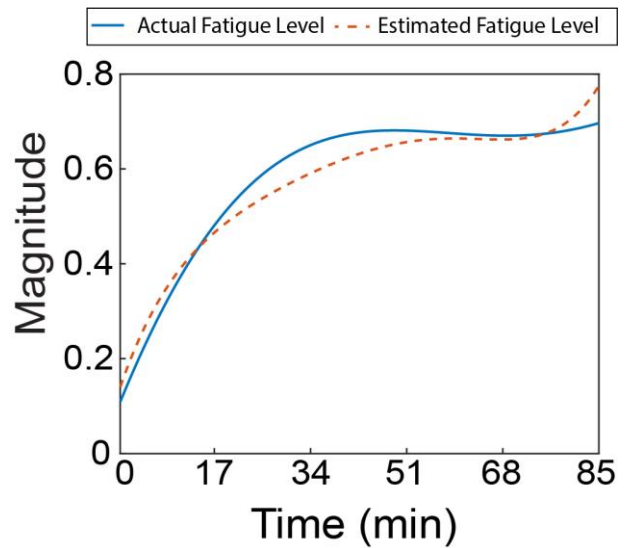

Fig. 6. Overall comparison between estimated fatigue level (obtained from SVR) and actual fatigue level (obtained from RT). The estimated fatigue level was obtained by using SVR with RBF kernel and 5 sec window length.

computational time were used in this study. Higher computational complexity would result in a delay in fatigue estimation which can lead to failure in preventing accidents in actual driving implementation.

Based on the results as shown in Fig. 3, the common channels that were shared across the majority (>95%) of the subjects were located in the frontal, parietal and occipital regions, which is consistent with the relevant regions for mental fatigue estimation identified in the previous papers (i.e., frontal region reported in [1, 12, 19], parietal region reported in [10, 19] and occipital region reported in [1, 11, 13, 14, 23, 38]). All aforementioned brain regions have also been detected by recent work [18]. In addition, even after reducing the number of electrodes by 75% for feature extraction, we still obtained similar performance compared to using all the electrodes. Therefore, effective fatigue estimation can be achieved by using few electrodes in the frontal, parietal and occipital regions (as shown in Fig. 3). Moreover, a head band can be developed with mounted electrodes that collects EEG signals only from the outer-ring region. Instead of a full headset, such a head band will be more practical to implement in a realistic scenario. Regarding the power bands, all the five bands i.e. delta [12, 13, 17-19, 39], theta [11-13, 15, 17-19, 40], alpha [11-14, 17-19, 23, 39, 40], beta [12, 13, 17, 19, 40] and gamma [18] band have been extensively used to extract spectral and connectivity features and measure mental fatigue. Hence, it can be concluded that there is no unique band which is dominant for distinguishing alertness from fatigue. Our current work also supports this point of view. All the spectral bands including the power ratios were found to be related to fatigue, and this was observed in at least 95% of the subjects.

To the best of our knowledge, this is the first work to

introduce DTW distance for performance evaluation of fatigue estimation. Unlike other similarity measures, DTW is flexible, as it is not based on exact data point mapping. This allows a more suitable comparison by providing the similarity measure in the trend between the signals.

We compared different regression models and window lengths and found that the SVR model with RBF kernel and 5 sec window length resulted in the best performance in estimation of the mental fatigue. For linear regression model, the window length did not significantly alter the performance and was least sensitive to window length compared to other regression models. On the contrary, quadratic regression was highly sensitive to the window length and gave the worst performance in terms of fatigue estimation performance. From Fig. 5, high variation was observed across subjects using all the electrodes with a standard deviation of 12.86. It is worth noting that these relatively high values of DTW distance for some subjects do not directly signify poor performance of the model. A slightly higher value could be obtained in some cases due to the difference in magnitude. This difference in magnitude persists because mental fatigue can be qualitatively measured and quantitative approximation of fatigue is not yet fully understood. Therefore, in this work, instead of finding a quantitative value of fatigue, the variation of the fatigue level from the alertness was observed. Hence, small differences in magnitude can give a slightly higher DTW value. However, the fatigue trend can be estimated correctly. As illustrated in Fig. 2(c), the signals are completely different and yielded a high DTW distance value of 161.98. Also, from Fig. 2(b) and 2(d), slight differences in phase and presence of local fluctuation give distance values less than 70. Taking these values as a reference, it can be concluded that, for all the subjects (as shown in Fig. 5), the estimated fatigue level from the regression model closely matches the actual fatigue level using the proposed framework.

In this study, we only employed spectral power features for fatigue estimation. Other features, such as functional connectivity [40, 41] and entropy [20, 42], could be used in the proposed framework as these features have been proven to be of discriminative power in the differentiation between alertness and fatigue. Most recently, high-order functional connectivity in both static and dynamic representations was found to have complementary information to low-order functional connectivity in fatigue detection [43]. These diverse kinds of features can be fused to improve fatigue classification [44]. In addition, transfer learning can be integrated with the proposed framework to enhance robustness of the performance across subjects and sessions [45].

V. CONCLUSION

In this work, we proposed a framework for practical real-time implementation of continuous fatigue estimation considering all the constraints associated with realistic driving. Unlike previous studies, we considered those constraints in our simulated driving environment so that the proposed framework can be seamlessly employed for fatigue estimation in real driving conditions. In this context, we used a wireless EEG headset with dry electrodes in this study, to reduce the preparation time and facilitate the practical use for drivers. Simple pre-processing steps were adopted to avoid high computational burden. Time was considered as the fatigue label and linearly correlated with the extracted features to select the relevant ones contributing to fatigue estimation. We proposed DTW distance as a similarity measure to evaluate the fatigue estimation performance due to its advantage of capturing the similarity in trend, neglecting minor local fluctuations and small differences between the estimated and actual fatigue level. RT was used only as a fatigue level indicator to validate our results and not as a feature to estimate fatigue level. Based on the comparative study of different regression models and window lengths, a combination of SVR with RBF kernel and 5 sec window achieved the best performance. Performance comparison with reduced number of channels showed similar performance and even better for about 45% of the subjects compared to that of using all electrodes. Our study showed that the proposed framework can be easily implemented in practical driving scenario to estimate fatigue level of drivers. This could help prevent potential traffic accidents caused by driving fatigue.

REFERENCES

[1]   C. Zhao, C. Zheng, M. Zhao, Y. Tu, and J. Liu, "Multivariate autoregressive models and kernel learning algorithms for classifying driving mental fatigue based on electroencephalographic," *Expert Systems with Applications,* vol. 38, pp. 1859-1865, 2011.

[2]   E. Grandjean, "Fatigue in industry," *Occupational and Environmental Medicine,* vol. 36, pp. 175-186, 1979.

[3]   S. K. Lal and A. Craig, "A critical review of the psychophysiology of driver fatigue," *Biological psychology,* vol. 55, pp. 173-194, 2001.

[4]   L. Fletcher, N. Apostoloff, L. Petersson, and A. Zelinsky, "Vision in and out of vehicles," *IEEE Intelligent Systems,* vol. 18, pp. 12-17, 2003.

[5]   A. Craig, Y. Tran, N. Wijesuriya, and H. Nguyen, "Regional brain wave activity changes associated with fatigue," *Psychophysiology,* vol. 49, pp. 574-582, 2012.

[6]   S. K. Lal, A. Craig, P. Boord, L. Kirkup, and H. Nguyen, "Development of an algorithm for an EEG-based driver fatigue countermeasure," *Journal of safety Research,* vol. 34, pp. 321-328, 2003.

[7]   A. Craig, Y. Tran, N. Wijesuriya, and P. Boord, "A controlled investigation into the psychological determinants of fatigue," *Biological Psychology,* vol. 72, pp. 78-87, 2006.

[8]   G. Borghini, L. Astolfi, G. Vecchiato, D. Mattia, and F. Babiloni, "Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness," *Neuroscience & Biobehavioral Reviews,* vol. 44, pp. 58-75, 2014.

[9]   X.-Q. Huo, W.-L. Zheng, and B.-L. Lu, "Driving fatigue detection with fusion of EEG and forehead EOG," in *Neural Networks (IJCNN), 2016 International Joint Conference on*, 2016, pp. 897-904.

[10]   C.-T. Lin, R.-C. Wu, T.-P. Jung, S.-F. Liang, and T.-Y. Huang, "Estimating driving performance based on EEG spectrum analysis," *EURASIP Journal on Applied Signal Processing,* vol. 2005, pp. 3165-3174, 2005.

[11]   C.-T. Lin, C.-J. Chang, B.-S. Lin, S.-H. Hung, C.-F. Chao, and I.-J. Wang, "A real-time wireless brain–computer interface system for

drowsiness detection," *IEEE Transactions on Biomedical Circuits and Systems,* vol. 4, pp. 214-222, 2010.

[12] L.-W. Ko, W.-K. Lai, W.-G. Liang, C.-H. Chuang, S.-W. Lu, Y.-C. Lu*, et al.*, "Single channel wireless EEG device for real-time fatigue level detection," in *Neural Networks (IJCNN), 2015 International Joint Conference on*, 2015, pp. 1-5.

[13] Y.-T. Liu, Y.-Y. Lin, S.-L. Wu, C.-H. Chuang, and C.-T. Lin, "Brain dynamics in predicting driving fatigue using a recurrent self-evolving fuzzy neural network," *IEEE transactions on neural networks and learning systems,* vol. 27, pp. 347-360, 2016.

[14] S. Pritchett, E. Zilberg, Z. M. Xu, M. Karrar, S. Lal, and D. Burton, "Strengthening association between driver drowsiness and its physiological predictors by combining EEG with measures of body movement," in *Broadband and Biomedical Communications (IB2Com), 2011 6th International Conference on*, 2011, pp. 103-107.

[15] D. Wu, V. J. Lawhern, S. Gordon, B. J. Lance, and C.-T. Lin, "Driver drowsiness estimation from EEG signals using online weighted adaptation regularization for regression (OwARR)," *IEEE Transactions on Fuzzy Systems,* 2016.

[16] S. Makeig and T.-P. Jung, "Tonic, phasic, and transient EEG correlates of auditory awareness in drowsiness," *Cognitive Brain Research,* vol. 4, pp. 15-25, 1996.

[17] C. Zhao, M. Zhao, Y. Yang, J. Gao, N. Rao, and P. Lin, "The reorganization of human brain networks modulated by driving mental fatigue," *IEEE journal of biomedical and health informatics,* vol. 21, pp. 743-755, 2017.

[18] W. Kong, Z. Zhou, B. Jiang, F. Babiloni, and G. Borghini, "Assessment of driving fatigue based on intra/inter-region phase synchronization," *Neurocomputing,* vol. 219, pp. 474-482, 2017.

[19] W. Kong, W. Lin, F. Babiloni, S. Hu, and G. Borghini, "Investigating driver fatigue versus alertness using the granger causality network," *Sensors,* vol. 15, pp. 19181-19198, 2015.

[20] R. Chai, G. R. Naik, T. N. Nguyen, S. H. Ling, Y. Tran, A. Craig*, et al.*, "Driver fatigue classification with independent component by entropy rate bound minimization analysis in an EEG-based system," *IEEE journal of biomedical and health informatics,* vol. 21, pp. 715-724, 2017.

[21] R. Chai, S. H. Ling, P. P. San, G. R. Naik, T. N. Nguyen, Y. Tran*, et al.*, "Improving eeg-based driver fatigue classification using sparse-deep belief networks," *Frontiers in neuroscience,* vol. 11, 2017.

[22] M. Azarnoosh, A. M. Nasrabadi, M. R. Mohammadi, and M. Firoozabadi, "Investigation of mental fatigue through EEG signal processing based on nonlinear analysis: Symbolic dynamics," *Chaos, Solitons & Fractals,* vol. 44, pp. 1054-1062, 2011.

[23] H. Wang, C. Zhang, T. Shi, F. Wang, and S. Ma, "Real-time EEG-based detection of fatigue driving danger for accident prediction," *International journal of neural systems,* vol. 25, p. 1550002, 2015.

[24] I. P. Bodala, N. I. Abbasi, Y. Sun, A. Bezerianos, H. Al-Nashash, and N. V. Thakor, "Measuring vigilance decrement using computer vision assisted eye tracking in dynamic naturalistic environments," in *Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE*, 2017, pp. 2478-2481.

[25] N. I. Abbasi, I. P. Bodala, A. Bezerianos, Y. Sun, H. Al-Nashash, and N. V. Thakor, "Role of multisensory stimuli in vigilance enhancement-a single trial event related potential study," in *Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE*, 2017, pp. 2446-2449.

[26] Y. Jiao and B.-L. Lu, "Detecting slow eye movement for recognizing driver's sleep onset period with EEG features," in *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the*, 2016, pp. 4658-4661.

[27] W. Li, Q.-c. He, X.-m. Fan, and Z.-m. Fei, "Evaluation of driver fatigue on two channels of EEG data," *Neuroscience letters,* vol. 506, pp. 235-239, 2012.

[28] M. G. Lak, M. R. Sabour, A. Amiri, and O. Rabbani, "Application of quadratic regression model for Fenton treatment of municipal landfill leachate," *Waste management,* vol. 32, pp. 1895-1902, 2012.

[29] A. Kazem, E. Sharifi, F. K. Hussain, M. Saberi, and O. K. Hussain, "Support vector regression with chaos-based firefly algorithm for stock market price forecasting," *Applied soft computing,* vol. 13, pp. 947-958, 2013.

[30] C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning,* vol. 20, pp. 273-297, 1995.

[31] Ö. Baydaroğlu, K. Koçak, and K. Duran, "River flow prediction using hybrid models of support vector regression with the wavelet transform, singular spectrum analysis and chaotic approach," *Meteorology and Atmospheric Physics,* pp. 1-11, 2017.

[32] H. Sakoe and S. Chiba, "A dynamic programming approach to continuous speech recognition," in *Proceedings of the seventh international congress on acoustics*, 1971, pp. 65-69.

[33] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," *IEEE transactions on acoustics, speech, and signal processing,* vol. 26, pp. 43-49, 1978.

[34] F. Petitjean, A. Ketterlin, and P. Gançarski, "A global averaging method for dynamic time warping, with applications to clustering," *Pattern Recognition,* vol. 44, pp. 678-693, 2011.

[35] F. Petitjean and P. Gançarski, "Summarizing a set of time series by averaging: From Steiner sequence to compact multiple alignment," *Theoretical Computer Science,* vol. 414, pp. 76-91, 2012.

[36] H. Izakian, W. Pedrycz, and I. Jamal, "Fuzzy clustering of time series data using dynamic time warping distance," *Engineering Applications of Artificial Intelligence,* vol. 39, pp. 235-244, 2015.

[37] R. Fu, H. Wang, and W. Zhao, "Dynamic driver fatigue detection using hidden Markov model in real driving condition," *Expert Systems with Applications,* vol. 63, pp. 397-411, 2016.

[38] C. Zhang, H. Wang, and R. Fu, "Automated detection of driver fatigue based on entropy and complexity measures," *IEEE Transactions on Intelligent Transportation Systems,* vol. 15, pp. 168-177, 2014.

[39] C.-T. Lin, C.-H. Chuang, C.-S. Huang, Y.-H. Chen, and L.-W. Ko, "Real-time assessment of vigilance level using an innovative Mindo4 wireless EEG system," in *Circuits and Systems (ISCAS), 2013 IEEE International Symposium on*, 2013, pp. 1528-1531.

[40] S. Charbonnier, R. N. Roy, S. Bonnet, and A. Campagne, "EEG index for control operators' mental fatigue monitoring using interactions between brain regions," *Expert Systems with Applications,* vol. 52, pp. 91-98, 2016.

[41] G. N. Dimitrakopoulos, I. Kakkos, A. G. Vrahatis, K. Sgarbas, J. Li, Y. Sun, & A. Bezerianos, "Driving Mental Fatigue Classification Based on Brain Functional Connectivity," in *International Conference on Engineering Applications of Neural Networks,* 2017, pp. 465-474.

[42] H. Wang, A. Dragomir, N. I. Abbasi., J. Li, N. V. Thakor, and A. Bezerianos, "A novel real-time driving fatigue detection system based on wireless dry EEG," *Cognitive neurodynamics*, vol. 12, pp. 365-376, 2018.

[43] J. Harvy, N. Thakor, A. Bezerianos, and J. Li, "Between-frequency topographical and dynamic high-order functional connectivity for driving drowsiness assessment," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 27, pp. 358-367, 2019.

[44] J. Harvy, E. Sigalas, N. Thakor, A. Bezerianos, and J. Li, "Performance Improvement of Driving Fatigue Identification Based on Power Spectra and Connectivity Using Feature Level and Decision Level Fusions," in the *40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018, pp. 102-105.

[45] J. He, G. Zhou, H. Wang, E. Sigalas, N. Thakor, A. Bezerianos, and J. Li, "Boosting Transfer Learning Improves Performance of Driving Drowsiness Classification Using EEG," in the *2018 IEEE International Workshop on Pattern Recognition in Neuroimaging (PRNI),* 2018, pp. 1-4.

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