Neurocomputing 311 (2018) 24–31

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Task-related EEG and HRV entropy factors under different real-world fatigue scenarios

Chin-Teng Lin[a], Mauro Nascimben[b], Jung-Tai King[b], Yu-Kai Wang[a,*]

[a] CIBCI Lab, Centre for Artificial Intelligence, FEIT, University of Technology Sydney, Australia
[b] Brain Research Center, National Chiao Tung University, Taiwan

ARTICLE INFO

Article history:
Received 13 November 2017
Revised 7 May 2018
Accepted 14 May 2018
Available online 19 May 2018

Communicated by Prof. Chunhui Zhao

Keywords:
Human performance
Entropy analysis
Alertness prediction
EEG
HRV
Psychomotor vigilance task

ABSTRACT

We classified the alertness levels of 17 subjects in different experimental sessions in a six-month longitudinal study based on a daily sampling system and related alertness to performance on a psychomotor vigilance task (PVT). As to our best knowledge, this is the first EEG-based longitudinal study for real-world fatigue. Alertness and PVT performance showed a monotonically increasing relationship. Moreover, we identified two measures in the entropy domain from electroencephalography (EEG) and heart rate variability (HRV) signals that were able to identify the extreme classes of PVT performers. Wiener entropy on selected leads from the frontal-parietal axis was able to discriminate the group of best performers. Sample entropy from the HRV signal was able to identify the worst performers. This joint EEG-HRV quantification provides complementary indexes to indicate more reliable human performance.

1. Introduction

Stress, fatigue, and sleep deprivation have each been demonstrated to affect human performance [1–3]. Being stressed or fatigued means that a person is over- or under-aroused and will not perform to the best of his/her ability. Early studies established the existence of an empirical relationship between performance and arousal. This relationship is usually referred to as the Yerkes–Dodson law [4]. This curvilinear performance-arousal relationship has been challenged by many other theories in the past. For some authors, performance on complex tasks degraded with increased arousal [5], while others suggested a linear relationship when task complexity was low [6].

Electroencephalography (EEG) provides a neurophysiological measure in situations where stress, mental fatigue and drowsiness are involved. In healthy people not experiencing stress, there is a balance between the sympathetic and parasympathetic arms of the autonomic nervous system. Stress causes activation of the emotional and vigilance systems, affecting the production of alpha waves [7] over frontal regions. When people become fatigued, they usually report difficulties concentrating and focusing on tasks that they are required to perform. EEG alpha and theta oscillations reflect cognitive and memory performance [8] and are possible markers of fatigue-induced changes. Drowsiness is easily detected through EEG by measuring the power spectrum in the alpha band at parieto-occipital sites [9].

By its nature, heart rate variability (HRV) provides an indicator of parasympathetic and sympathetic balance. HRV modifications in low-frequency (LF, 0.04 to 0.15 Hz) and high-frequency (HF, 0.15 to 0.4 Hz) domains are associated with stress exposure. A reduction in the high-frequency component of HRV and an increase in the low-to-high-frequency ratio were observed in the stress condition compared with those in the control condition [10] in a mental workload study. Modifications of the LF/HF ratio were also noted by another study [11] on mental stress. A test of mental fatigue after a long arithmetic task showed that total power, low-frequency power and the LF/HF ratio increased after the task [12]. Drowsiness was measured in car drivers by HRV in a recent study [13]. The authors reported increased HF and decreased LF and LF/HF ratio in comparison with the initial values before driving. Laboratory findings on drivers' alertness and drowsiness can be generalized to real-world situations [22].

The correlation between electroencephalography and heart rate variability has been investigated during sleep [14], and one short-term study also examined its modulation during event-related attention shifts [15]. This last study focused on time and frequency parameters from the HRV signal and frequency parameters from EEG signals in the alpha and theta bands. We designed a

* Corresponding author.
E-mail addresses: yukaiwang@cs.nctu.edu.tw, windson.iie96g@g2.nctu.edu.tw (Y.-K. Wang).

https://doi.org/10.1016/j.neucom.2018.05.043

similar study with a different approach. Specifically, we sought to analyze how hemispheric attentional shifts and cardiovascular parameters relate to human performance at different levels of fatigue.

Interactions between EEG- and electrocardiography (ECG)-derived measures have also been proposed in hybrid brain-computer interface (BCI) systems [15,16]. BCIs translate brain intentions into commands deliverable to a machine. Usually, non-invasive BCI uses EEG as its main data source. Hybrid BCIs combine a different kind of physiological signal with EEG to improve the overall performance. The combination of EEG with ECG signals has been proposed to improve classification accuracy in motor imagery (MI) [16]. This goal could be achieved using an experimental paradigm with HRV, taking advantage of the increased respiratory and cardiac activity during task execution. For example, in the case of MI, subjects who have the ability to vividly imagine the limb movement also display a significant shift in HRV. The involvement of the subject is also increased in the case of virtual reality experiments where the subject is immersed in the environment and emotions are heightened. However, stress and emotion also cause heart rate changes. The impact of these changes could be reduced using an adaptive autoregressive filter. For BCIs, it may also be possible to take advantage of such changes associated with user stress level. If the stress level detected through heart rate rises above a certain threshold and causes the user's performance to change, this phenomenon could be interpreted by the machine as a warning signal associated with the decision to recalibrate the system. In fact, performance stability over time is an unresolved issue with BCIs. A hybrid EEG/HRV system that adapts to user mental state could be useful for achieving performance stability.

In the field of adaptive BCIs, an approach using brain entropy was proposed recently [17]. The authors' hypothesis was that performance would decrease over multiple sessions, caused by a lack of novelty in the stimuli. In fact, according to Bayesian cognitive science, there should be a relationship of some sort between brain energy expenditure and novelty. The authors argue that BCI systems could take advantage of this relation, which relates directly to inter-session performance decay in many machine learning algorithms. A possible application of this principle is that BCI paradigms could adjust the level of interaction with the user according to his/her cognitive state. Theoretically, brain entropy and its relation to cognitive workload or attentional orientation could be used not only to change the information level streaming to the user in BCI systems but also to build a bidirectional communication channel between humans and machines though brain state manipulation.

In this study, we conducted a psychomotor vigilance task (PVT) with 17 subjects to measure their fatigue level while simultaneously measuring EEG and HRV correlates of their performance. Entropy was then calculated through the acquired EEG and HRV data. Our goal was to find a way to measure event-related attention and monitor HRV changes to build a complete framework incorporating neurophysiological variables affected by fatigue and to describe the overall impact of these variables on performance.

2. Materials and methods

Twenty-two students attending National Chiao Tung University (Hsinchu, Taiwan) were recruited to participant this longitudinal study for continuous six months. Five subjects were unable to complete all sessions of this experiment and were not included in this study. Included participants were 13 males and 4 females, aged 22.4 ± 1.5. Their fatigue level was monitored using an E3 wristband (Fatigue Science, USA) with effectiveness scores as outcomes [18]. Effectiveness scores are an output number from the SAFTE algorithm (proprietary, Fatigue Science, USA) based on the parameters extracted from the E3 smart-watch, mainly actigraphy for sleep evaluation. Relevant sleep factors included acute sleep interruptions, cumulative sleep debt, and the consistency of sleep onset and wake times. In a previous study, E3 resolution in sleep detection was compared with standard clinical polysomnography and reached 92% accuracy [18]. However, the E3 wristband also records other physiological parameters, such as heart rate and galvanic skin response. These additional parameters contribute to the SAFTE algorithm for fatigue detection, integrating sleep data with homeostatic and circadian rhythm and considering their influence on cognitive functions. The ES index is a continuous output from the SAFTE algorithm that uses data gathered over a period of three days. For this reason, subjects wore the smart watch throughout the longitudinal experiment, even at home. Each day, the subjects' ES at wake time was collected and sent to a cloud server. Participants received notifications through text message to come in to the laboratory for the PVT experimental trial within 12 hours if the ES score was suitable for an experimental session. Initially, the ES score at wake time was classified into three classes corresponding to well-rested (normal state), sleep-deprived (a high-fatigue level) or sleep–restricted states (a low-fatigue level). Based on SAFTE guidelines, we classified the wake-time ES into the normal class if the effectiveness score was in the 90–100% range, the well-rested state if ES was in the 70–90% range and the sleep-deprived state if ES was below 70%. Subjects performed the PVT test three times for each class. We divided the starting time of the experiment into three time slots (morning, afternoon and evening). Each recording of each class started at a different time.

For each subject, we recorded two EEGs: one before starting the PVT test and another during the PVT test. EEG was recorded with a Neuroscan SynAmps 2 64-channel device using extracephalic reference A1 and a sampling frequency of 500 Hz. Before starting the experiment, three minutes of free-running EEG were recorded with the subject's eyes open to assess individual baseline activity. Each participant sat in front of a desktop computer and completed ten minutes of the PVT paradigm. Subject reaction time was measured according to a button press after the appearance of a red dot in the center of the screen. All subjects were right-handed, and they pressed the response button with their dominant hand. In this way, we tried to reduce the impact of movement artifacts on E3 signals. A response was regarded as 'valid' if the reaction time (RT) was between 100 ms and 1.2 seconds; otherwise, the response was recorded as a lapse. For performance calculation, an RT of less than 500 ms was accepted as a 'correct' response. HRV was extracted from the E3 Readiband photoplethysmographic waveforms recorded from the left wrist.

Preprocessing and analysis were carried out in a MATLAB environment under an academic license. Preprocessing of photoplethysmographic data included removal of ectopic beats, trend removal and resampling. For ectopic beat removal, an HRV value higher than 20% of the previous value was considered a disturbance of the cardiac rhythm and was substituted with the median of all subjects' adjacent HRV points. The signal after trend removal was resampled at 16 Hz.

EEG preprocessing included an initial finite impulse response (FIR) bandpass filter in the range of 1–45 Hz. Artifactual sources were removed by independent component analysis (ICA) decomposition using EEGLAB [19], and after back-projection, the frequency content of the EEG signals was further reduced in the range of 4–30 Hz. The frequencies included in the analysis were the theta, alpha and lower/higher beta bands. We included drowsiness indicated by theta (4–8 Hz), relaxed wakefulness indicated by alpha (8–12 Hz), alertness indicated by lower beta (13–20 Hz) and intense mental activity indicated by higher beta (20–30 Hz).

During PVT, one second before the appearance of the dot was considered the EEG epoch of maximal alertness for the participants. During this period, we expected to find a peak in alertness, namely, the time when the probability of the dot appearing on screen was maximal. The subjects were instructed to press the button quickly after the appearance of the dot. We named this epoch “attentional climax” and compared it with the baseline activity on the resting EEG. For this comparison, we selected Wiener entropy as an index of attentional shifts from the resting EEG.

Wiener entropy [20] (WE) is a measure of the complexity of a system, describing its degree of organization. An EEG application using the same 1 s time window has already been discussed in a paper by Burns at el. [21]. The Wiener entropy of the power spectrum during attentional climax and resting EEG was obtained through the following formula:

$$W\ E = \frac{exp\left(\sum_{n=0}^{N-1} ln\ x(n)\right)}{\frac{1}{N}\sum_{n=0}^{N-1} x(n)}$$

where *x(n)* represents the magnitude of bin number *n*. Wiener entropy tends to zero when the spectral distribution of the frequency band exhibits a salient peak and is equal to one when the spectral distribution of the frequency band is flat. For each electrode, the index Wiener entropy = attentional climax/resting EEG was calculated and averaged for all PVT epochs. The resting EEG was adjusted to the same time window as attentional climax, averaging 1 s epochs.

According to a literature review of the influence of mental fatigue on EEG signals, the main brain areas involved are the frontal electrodes near the midline and one or more parietal areas, with a reported lateralization around electrodes P7 and P8 [22–27]. Considering that EEG activity reflects the neural activity of brain areas more effectively than the activation of a single electrode, we decided to include three electrodes to provide more consistent findings than a single-electrode study could. We selected three electrodes for each of these areas (frontal right, frontal left, parietal left and parietal right) and built an index based on the hemispheric differences as shown in the following figure. In this study, AF3, F3, and F1 were selected to represent the mid-frontal area in the left hemisphere. Electrodes AF4, F4 and F2 represented the right frontal area. Electrodes TP7, P7 and P5 represented the left parietal area. Electrodes TP8, P8 and P6 represented the right parietal region.3 Fig. 1

We chose an electrode montage according to these observations so that we could average the Wiener entropy indexes from frontal and parietal electrodes, as shown in the following formulas.

$$Left\ Hemisphere = \frac{mean(W.E.index\ F3 +\ W.E.index\ AF3 +\ W.E.index\ F1)}{mean(W.E.index\ P7 +\ W.E.index\ P5 +\ W.E.index\ TP7)} \quad \text{(A)}$$

$$Right\ Hemisphere = \frac{mean(W.E.index\ F4 +\ W.E.index\ AF4 +\ W.E.index\ F2)}{mean(W.E.index\ P8 +\ W.E.index\ P6 +\ W.E.index\ TP8)} \quad \text{(B)}$$

Dividing the results from the left [A] and right side [B] of the scalp over the mid-frontal and lateral parietal regions is also consistent with previous findings [28] on visuospatial attention. In this way, we could show lateralized hemispheric functionality changes in relation to fatigue across important attention-related regions. Models of arousal level in emotion detection [29] or attention [30] include asymmetric indexes based on frontal EEG. The close relation between arousal and the subject’s psychological state could be captured by the frontal components of our index.

For HRV, we used sample entropy (SE) to investigate cardiovascular dynamics. Sample entropy is already a tested measure of HRV complexity, and we followed the approach suggested in an article by Richman et al. [31]. SE was calculated over the whole 10-min PVT experiment.

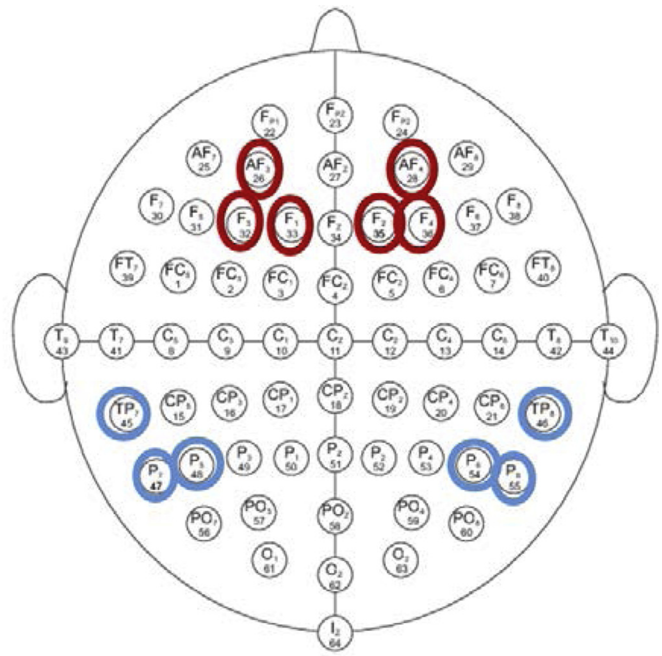

Fig. 1. 64 Channels and the electrode position system used in the experiment to acquire the EEG signals. The highlighted electrodes are from frontal (red) and lateral parietal areas (blue) used to build the W.E. index (formulas [A] and [B]). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
GROUP DEFINITIONS.

	Group definitions		
	Group Description	*Label*	*Group size*
ES > “Mean + SD”	Best alertness	BA	12
“Mean” > ES > “Mean + SD”	Above mean alertness	AM	50
“Mean-SD” < ES < “Mean”	Under mean alertness	UM	28
ES < “Mean-SD”	Worst alertness	WA	19

Each PVT session for each subject was labelled according to the effectiveness score returned by the SAFTE model to quantify alertness/fatigue measured at arrival in the laboratory right before starting the PVT test. In this way, we had an evaluation of the fatigue/alertness level of the subject closer to when the PVT test was administered. We used four classes to obtain better resolution and understanding of the impact of fatigue on human performance. Table 1 summarizes the four group labels established by comparing the single ES of each recording with the mean and standard deviation (SD) of all ES values stored for all 153 recordings.

Although we ran nine sessions with different starting times, the finding days on which ES reflected an extreme (BA or WA) alertness level was difficult. Consequently, the group sizes were different, which could decrease the statistical power of the tests. For this reason, we carefully selected statistical measures compatible with unequal group sizes. Paired *t*-tests of ES, corrected for unequal group sizes, were significant for all pairwise comparisons between groups. Furthermore, a between-group ANOVA ($F = 170.6658$, $p = 3.1514 \times 10^{-40}$) and post hoc *t*-tests with Bonferroni correction showed significant differences between all pairs of groups. ANOVAs were performed as a one-way analysis of variance. With these ANOVA tests, we tested the hypothesis that the samples were drawn from populations with the same mean against the alternative hypothesis that the population means were not all the same.

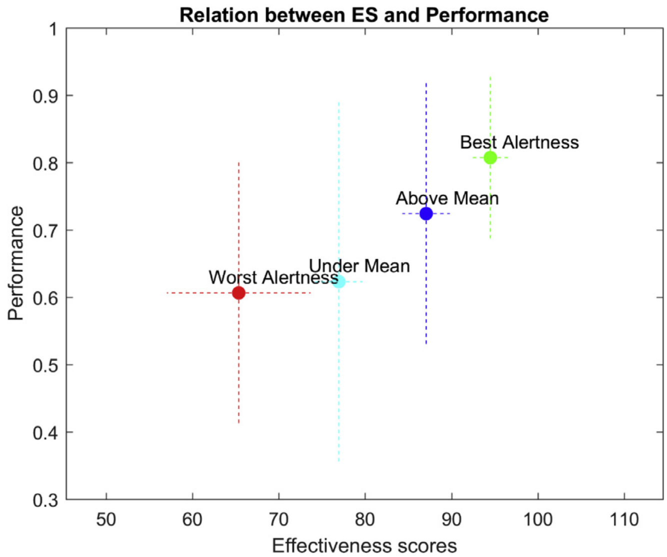

Fig. 2. Relation between ES (*x*-axis) and PVT performance (*y*-axis) for the four groups. The arms of the crosses are standard deviations on the *x*- and *y*-axes. The center of the crosses is the bivariate mean.

3. Results

3.1. Performance

PVT performance was calculated as the percentage of correct button presses out of valid responses, as explained in the Methods section. The relation between performance and alertness is shown in Fig. 2.

Paired *t*-tests of PVT performance indicated significant differences between the BA and UM groups ($t=2.9827$, $p=0.0050$), AM and WA groups ($t=2.2387$, $p=0.0321$), and BA and WA groups ($t=3.5568$, $p=0.0013$). The relation between performance and ES appeared to be approximately quadratic. There was also a significant difference between groups in PVT performance in the one-way ANOVA ($F=3.5693$, $p=0.0166$).

3.2. EEG

Wiener entropy in the left hemisphere was significantly related to between-group differences as tested by a balanced one-way ANOVA ($\mathrm{F}=4.2122$, $\mathrm{p}=0.0074$) and within-group differences using post hoc Bonferroni correction between BA and AM groups ($p=0.0324$), BA and UM groups ($p=0.0052$), and BA and WA groups ($p=0.0228$). Fig. 3 plots EEG-derived Wiener entropy against PVT performance. Paired *t*-tests of W.E. showed significant differences between the BA and UM groups ($t=-3.5165$, $\mathrm{p}=0.002$), BA and AM groups ($t=-2.8906$, $p=0.0097$) and BA and WA groups ($t=-3.2568$, $p=0.0038$). T-tests between the AM and WA groups ($t=-0.7403$, $p=0.4632$), WA and UM groups ($t=-0.3409$, $p=0.7348$) and UM and AM groups ($t=-1.1111$, $p=0.2711$) were not significant.

W.E. in the right hemisphere did not reach statistical significance ($F=1.3808$, $p=0.2528$). A similar result with a prevalent left hemispheric effect (but only in alpha band) caused by mental fatigue was found in [32] on prolonged Stroop task. Sun et al. applied PVT (intra-session analysis) to demonstrate the asymmetrical pattern of connectivity (right > left) in fronto-parietal regions associated with sustained attention, supporting the right-lateralization of this function [33]. Interestingly, in the fatigue state, significance decreases were observed in left, but not right fronto-parietal connectivity. This last result is compatible with our findings on W.E. hemispheric index that changes significantly over left regions in this longitudinal study.

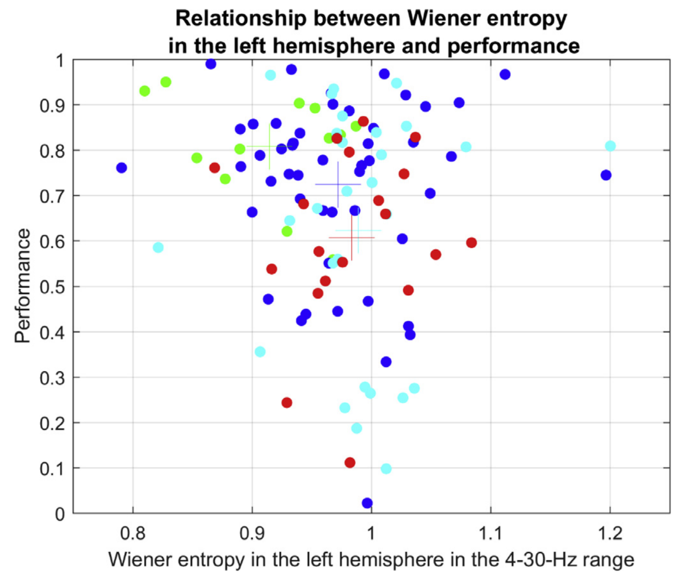

Fig. 3. Relationship between PVT performance and WE in the left hemisphere. Legend: BA (green), AM (blue), UM (cyan), WA (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

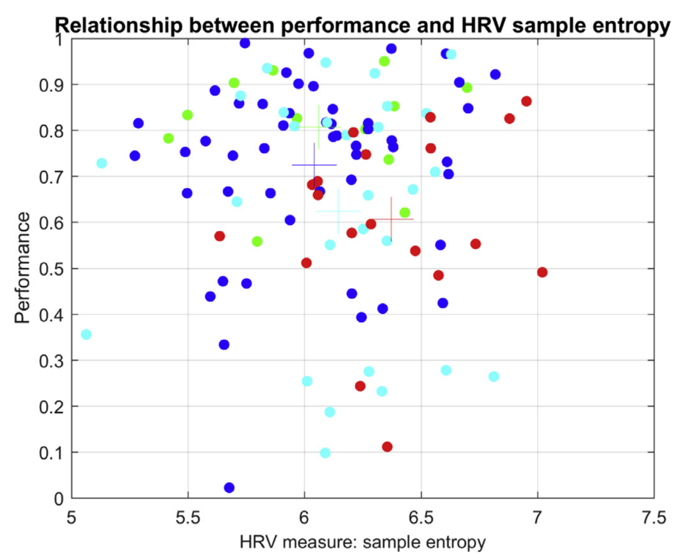

Fig. 4. Relationship between HRV sample entropy and PVT performance. Legend: BA (green), AM (blue), UM (cyan), WA (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3. HRV

In terms of sample entropy, there was a significant difference between groups as tested by a balanced one-way ANOVA ($F=3.4869$, $p=0.0184$), and there was also a significant within-group difference between the AM and WA groups ($p=0.0122$) using post-hoc tests with Bonferroni correction. The following figure displays the relationship between PVT performance and sample entropy (Fig. 4).

Paired *t*-tests of SE showed significant differences between the AM and WA groups ($t=-3.3382$, $p=0.002$), WA and UM groups ($t=2.0207$, $p=0.0498$) and BA and WA groups ($t=-2.1655$, $p=0.0418$). Other comparisons did not reach significance (BA *vs*

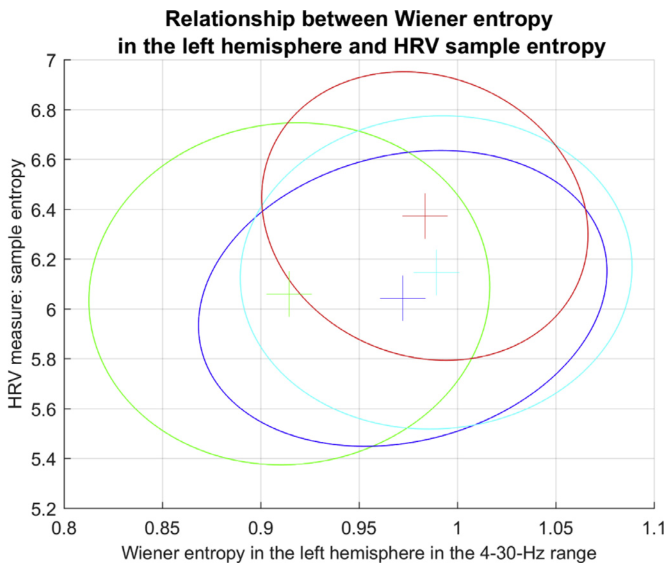

Fig. 5. Joint analysis between WE and HRV SE. Data are rendered as confidence ellipses (confidence level 68%). Legend: BA (green), AM (blue), UM (cyan), WA (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Summary of results.

	ES	Performance	WE left hemi.	SE
BA	94.5000 ± 2.1110	0.8073 ± 0.1197	0.9146 ± 0.0607	6.0601 ± 0.4089
AM	87.0720 ± 2.7501	0.7242 ± 0.1965	0.9722 ± 0.0673	6.0419 ± 0.3846
UM	76.9500 ± 2.7439	0.6231 ± 0.2709	0.9892 ± 0.0633	6.1459 ± 0.3997
WA	65.3579 ± 8.3185	0.6065 ± 0.1947	0.9835 ± 0.0516	6.3722 ± 0.3603

UM, $t = -0.6120$, $p = 0.5472$; AM *vs* UM, $t = -1.1175$, $p = 0.2687$; AM *vs* BA, $t = 0.1404$, $p = 0.8901$). The relationship between the WE index in the left hemisphere and the HRV SE during the PVT test is plotted in Fig. 5.

While the BA and WA groups could be drawn on a straight line, the middle groups had a non-linear relationship. What emerges from the figure is the possibility of using W.E. (x-axis) to discriminate the best performers from others and the possibility of using SE (y-axis) to identify the worst performers. Jointly, WE and SE identified the extreme groups.

The results of sections A, B and C are summarized in Table 2.

After these steps, we can conclude that WE and SE reflect two different behaviors within the four groups. Wiener entropy is more effective than SE in describing the differences between the best performers (BA) and others. In contrast, sample entropy is the better of the two measures for differentiating the worst performers from others. Together, these two indicators are able to represent shifts between alertness and fatigue and their influence on performance.

Linear dependence was investigated through correlations among the four performance variables, WE from our montage on the left hemisphere, SE and alertness level as quantified by ES. Table 3 shows the correlation coefficients, with significant values marked by an asterisk. Effectiveness scores are shown in relation to other variables. These correlations may be useful in future studies because they can indicate the relationship between alertness levels and other measurements.

We can change the point of view and analyze the results from the subjects' alertness levels. Multivariate analysis of variance using the EEG entropy-based index, HRV sample entropy and performance as factors returned 1 dimension ($p = 0.0003$), rejecting the null hypothesis that any difference observed in the sample

Table 3
Correlation coefficients.

	Linear Correlation			
	ES	Perf.	WE	SE
ES	1	0.2854(*)	−0.2008(*)	−0.2781(*)
Perf.	0.2854(*)	1	−0.0957	−0.0009
WE	−0.2008(*)	−0.0957	1	0.1164
SE	−0.2781(*)	−0.0009	0.1164	1

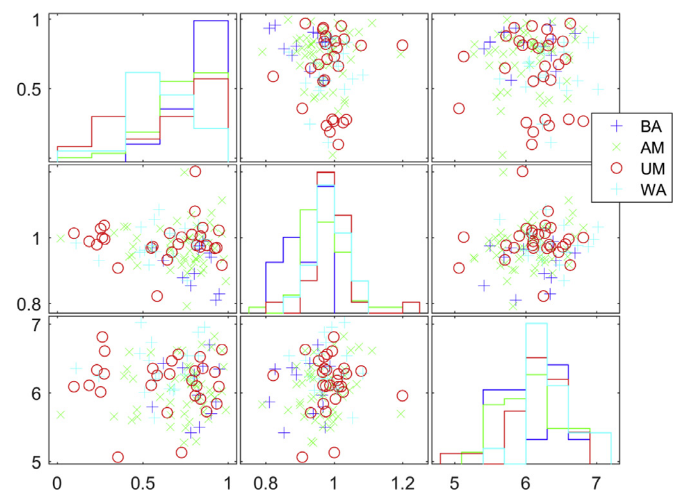

Fig. 6. The *x*-axis from left to right shows performance, WE and SE. The *y*-axis from top to bottom shows performance, WE and SE.

was due to random chance. These results suggest that the group means were different but linearly related. The variations in these factors move together following a straight trajectory, with different groupings along this trajectory representing different alertness levels. This finding is compatible with the relationship previously described between performance and alertness. A complete view of each factor is shown as an array of scatter plots in Fig. 6.

4. Discussion

In our work, we found that measures of entropy from EEG and HRV could, when used together, describe the relationship between performance and alertness. Entropy in EEG signals, calculated as Wiener entropy from baseline, was able to identify groups of individuals with higher levels of alertness. Conversely, sample entropy could identify groups with low levels of alertness. We performed a PVT experiment and found that there was a relation between alertness level and performance outcome: the higher the alertness, the better the performance. Consequently, higher WE and lower SE were able to detect the best and worst performers in the experiment. Our results aren't influenced by emotional, anxiety or stress factors typical of an intellectually demanding task requiring endurance and persistence from the subjects in the current experiment design. For this reason, a straightforward interpretation of results is possible similarly to a monotonically increasing trend (linear or exponential) performance-arousal. A different article [34] proposed a mathematical method to correlate increases in heart rate that follow mental arousal level. The authors reported a monotonically increasing function correlating those two measures similarly to what we show in Fig. 4 of our paper. In Fig. 4, we derived a sample entropy index from heart rate and showed a non-linear trend related to performance. EEG entropy analysis is a well-established methodology of analysis in modern neuroscience. We reported in the Introduction of the paper the theories about entropy in an energy-spending system, similar to in our brain, and its relation to the novelty of the stimulus. Here, we can add that a different paper [35] reported findings using emotion analysis. Emotions are related to arousal level because emotional strength modulates the subjective arousal state. The authors calculated quadratic entropy (derived from sample entropy) and used it to determine the complexity or irregularity of EEG signals under differently elicited degrees of arousal. Non-linear analysis of entropy seems to be a good indicator of the brain's working dynamics under different arousal levels. In their results, the authors found that states of excitement produced lower entropy levels than calm states. In our paper, we based our non-linear analysis on the hemispheric Weiner entropy index. According to our results, we also found a non-linear trend from the lowest alertness to the highest alertness levels as shown in Fig. 3 in the Results section.

Wiener entropy modifications were significant mainly in the left hemisphere electrodes of the chosen montage. This finding could be explained by the involvement of the left hemisphere in executing familiar actions [36] for efficient handling of routine situations. The PVT is a routine task in which the subject is instructed to press a button as quickly as possible when a "go" signal appears. All subjects in the present study were right-handed, but we do not think motor commands influenced our findings in the mid-frontal and lateral parietal areas. One reason for this conclusion is that we were analyzing what we defined as "attentional climax", which occurs before the delivery of the motor signal. Furthermore, we avoided motor-related areas when choosing electrode sites for our montage.

This study confirmed that alertness correlates with PVT performance within a testing session, as found in a recent investigation [37]. We observed that the relationship between alertness level described by effectiveness scores and performance was not linear. The mean points seemed to fall on a slowly increasing non-linear curve. In terms of the empirical relationship between arousal and performance, this finding appears to contradict the Yerkes–Dodson law [38] and seems more in accordance with drive theory [39]. Drive theory is a theory of arousal that proposes a linear relationship between arousal and performance where, as arousal increases, so does the quality of performance. Many papers in the scientific literature debate the different performance-arousal relationships and have proposed new theories. The debate continues today. In a recent Neuron paper, McGinley et al. (2015) [40] investigated the link between arousal state and behavioral performance and demonstrated neural correlates of an "optimal" state for an auditory detection task in mice. The authors demonstrated that, following a Yerkes-Dodson curve, the relationship between membrane potential and arousal is a U curve, as is the variability in membrane potential. In their approach mice, were not restricted to periods of high performance, but they were allowed to drift between behavioral states, which enabled the authors to map out a continuum of arousal. This approach provides a clear demonstration that just because an animal is awake and performing, it is not in a specific, well-defined state. In our study, we used the same principle, recording subjects at different alertness levels (using ES) and at different moments in the day. Our experiment involving human subjects at certain moments of their real-world life is even more appropriate than those involving captive mice whose life is restricted to cages. Electroencephalogram offers a reliable neural correlate of human brain activity. However, in our findings with humans, the alertness-performance relationship was better modeled by drive theory than an inverted U-shape.

Considering the significant differences in performance, we conclude that WE in the left hemisphere can identify the best PVT performers, whereas the HRV SE can identify the worst performers. Past studies also showed a relationship between performance and measured brain activation, but here, we characterized which parameters differentiated the best and worst performance from the nearest "average" level, dividing the broad average group in two subsets.

A possible future application of this study could be the translation of our findings into a longitudinal monitoring system consisting of a hybrid BCI device. A crucial issue in BCIs is the variation in performance within the same subject across different sessions. A monitoring system for the entropy domain for both EEG and HRV signals could track human performance and adapt the system to the user's cognitive state. Adaptation could be achieved by changing the information flow to the user. In the interest of saving computational resources in the BCI system, it could be limited to HRV oscillations. In our case, HRV correlated with the shift in user performance from the below-mean to the worst alertness class. We classified the lowest level of alertness as WA. Our ability to identify this category by HRV means the BCI system can recognize critical performance degradation and warn the subject to rest. A recalibration for this BCI system could also be necessary when user's performance is too low. Fluctuations in alertness could be compensated by the system slowing down or increasing the data flow to the user. This adaptive BCI paradigm could also adjust the training of the classifier "on the fly", adapting the underlying classifier model. In fact, one goal for actual BCI systems is to autocalibrate, skipping the initial training phase for the classifier. An alternative could be to use the HRV channel as a "switch" for hybrid BCIs. When the subject reaches the lowest alertness level as detected by HRV, the BCI system could change modality. For example, it could change from a synchronous (cue-based) to an asynchronous (self-paced) mode. This modality shift could restore higher user performance for a limited period of time, maintaining the compliance of the device. The functionality of the system might decay after the user performed the task for an extended time. Nonetheless, the system could still continue to run beyond the expected time. Some futuristic visions of BCI systems target them toward human brain enhancement. In this case, the outcomes during the highest performance peak (our BA class in Table 2) could be monitored and stored. When the subject is in a performance class near his/her mean (AM or UM in Table 2), the system could fill the gap between actual performance values and the values recorded during the best period. In this way, the system could be operated as a performance enhancer for the user. This application could be mainly targeted toward BCI usage in normally abled users. Another application of joint EEG and HRV analysis could be driver fatigue detection: fatigue in drivers is not directly measurable but inferred from other sources of information. EEG- and HRV-related changes could be modeled as a neural network able to simulate the brain's behavior under different fatigue levels. A similar concept was explored previously [41] where they modeled a Bayesian network to recognize driver mental states. The difference with our study is that authors also used eye tracking to obtain more insights into alertness state. Eye tracking could be an important parameter to refine our findings and experiments.

5. Conclusions

This study applied joint analysis of entropy in EEG signals and HRV under varying real-world fatigue states. Seventeen subjects participated six-month longitudinal study for monitoring the real-world fatigue levels through daily sampling system. As to our best knowledge, this is the first EEG-based longitudinal study for real-world fatigue. According to the statistic and correlation analyses, WE of EEG signals is a stable index to identify BA group, and SE of HRV can stably represent the changes in WA group. This work suggests the joint EEG-HRV quantification provides complementary indexes for a reliable indication of human performance and how performance is influenced by different arousal or fatigue levels. These indicators could have a practical application in real-life activities.

Acknowledgments

This work was supported in part by the Australian Research Council (ARC) under discovery grant DP180100670 and DP180100656. Research was also sponsored in part by the Army Research Laboratory and was accomplished under Cooperative Agreement Numbers W911NF-10-2-0022 and W911NF-10-D-0002/TO 0023. The views and the conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S Government. The U.S Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein

References

[1] James E. Driskell, Salas Eduardo (Eds.), Stress and Human Performance, Psychology Press, 2013.
[2] Centers for Disease Control and Prevention (CDC). "Short sleep duration among workers–United States, 2010." MMWR. Morbidity and mortality weekly report 61.16 (2012): 281.
[3] M.A. Staal, Stress, cognition, and human performance: A literature review and conceptual framework (NASA report/TM-2004-212824), 2004.
[4] R.A. Cohen, Yerkes–Dodson Law, Encyclopedia of Clinical Neuropsychology, Springer, New York, 2011, pp. 2737–2738.
[5] W.R. Lovallo, Stress and health: Biological and Psychological Interactions, Sage publications, 2015.
[6] S.M. Arent, D.M. Landers, "Arousal, anxiety, and performance: a reexamination of the inverted-U hypothesis, Res. Q. Exerc. Sport 74 (4) (2003) 436–444.
[7] R.S. Lewis, N.Y. Weekes, T.H. Wang, "The effect of a naturalistic stressor on frontal EEG asymmetry, stress, and health, Biol. Psychol. 75 (3) (2007) 239-247. [8] Klimesch, Wolfgang. "EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis." Brain research reviews 29.2 (1999): 169-195.
[8] W. Klimesch, EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis, Brain Res. Rev. 29 (2) (1999) 169–195.
[9] R.B. Berry, et al., The AASM manual for the scoring of sleep and associated events, Rules, Terminology and Technical Specifications, American Academy of Sleep Medicine, Darien, Illinois, 2012.
[10] N. Hjortskov, et al., "The effect of mental stress on heart rate variability and blood pressure during computer work, Eur. J. Appl. Physiol. 92 (1-2) (2004) 84–89.
[11] J. Taelman, et al., Influence of mental stress on heart rate and heart rate variability, in: Proceedings of the Fourth European Conference of the International Federation For Medical and Biological Engineering, Springer, Berlin Heidelberg, 2009.
[12] C. Zhang, X. Yu, "Estimating mental fatigue based on electroencephalogram and heart rate variability, Pol. J. Med. Phys. Eng. 16 (2) (2010) 67–84.
[13] W.C. Liang, et al., "Variation in Physiological parameters before and after an in--door simulated driving task: effect of exercise break, in: Proceedings of International Conference on Gerontic Technology and Service Managemer, Nantou County, Taiwan, 2007.
[14] M. Ako, T. Kawara, S. Uchida, S. Miyazaki, K. Nishihara, J. Mukai, Y. Okubo, Correlation between electroencephalography and heart rate variability during sleep, Psychiatry Clin. Neurosci. 57 (1) (2003) 59–65.
[15] S.K. Yoo, C.K. Lee, Changes in EEG and HRV during event-related attention, Int. J. Med. Health Biomed. Bioeng. Pharm. Eng. 7 (10) (2013).
[16] G. Pfurtscheller, B.Z. Allison, C. Brunner, G. Bauernfeind, T. Solis-Escalante, R. Scherer, N. Birbaumer, The hybrid BCI, Front. Neurosci. 4 (2010) 42–45.
[17] S.W. Hincks, S. Bratt, S. Poudel, V.V. Phoha, R.J.K. Jacob, D.C. Dennett, L.M. Hirshfield, Entropic brain-computer interfaces using fNIRS & EEG to measure attentional states in a Bayesian framework, in: In PhyCS 2017 - Proceedings of the 4th International Conference on Physiological Computing Systems, SciTePress, 2017, pp. 23–34.
[18] S.R. Hursh, D.P. Redmond, M.L. Johnson, D.R. Thorne, G. Belenky, T.J. Balkin, W.F. Storm, J.C. Miller, D.R Eddy, Fatigue models for applied research in warfighting, Aviation Space Environ. Med. 75 (2004) A44–A53 Supplement 1.
[19] A. Delorme, S. Makeig, EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis, J. Neurosci. Methods 134 (1) (2004) 9–21.
[20] N. Wiener, The Human Use of Human beings: Cybernetics and Society, Mifflin, Boston Houghton, 1954, pp. 15–27.
[21] T. Burns, R. Rajan, Combining complexity measures of EEG data: multiplying measures reveal previously hidden information, F1000Research 4 (2015) 137.
[22] S.H. Fairclough, L. Venables, A. Tattersall, The influence of task demand and learning on the psychophysiological response, Intl. J. Psychophysiol. 56 (2004) 171–184.
[23] A. Gevins, M.E. Smith, Detecting transient cognitive impairment with EEG pattern recognition methods, Aviation Space Environ. Med. 70 (1999) 1018–1024.
[24] A. Gevins, M.E. Smith, L. McEvoy, D. Yu, High-resolution EEG mapping of cortical activation related to working memory: Effects of task difficulty, type of processing, and practice, Cereb. Cortex 7 (1997) 374–385.
[25] T.C. Hankins, G.F. Wilson, A comparison of heart rate, eye activity, EEG and subjective measures of pilot mental workload during flight, Aviation Space Environ. Med. 69 (1998) 360–367.
[26] M.E. Smith, L.K. McEvoy, A. Gevins, The impact of moderate sleep loss on neurophysiologic signals during working-memory task performance, Sleep 25 (2002) 784–794.
[27] L. Trejo, K. Knuth, R. Prado, R. Rosipal, K. Kubitz, R. Kochavi, ..., Y. Zhang, EEG-based estimation of mental fatigue: convergent evidence for a three-state model, in: Foundations of augmented cognition, 2007, pp. 201–211.
[28] P. Sauseng, W. Klimesch, W. Stadler, M. Schabus, M. Doppelmayr, S. Hanslmayr, N. Birbaumer, A shift of visual spatial attention is selectively associated with human EEG alpha activity, Eur. J. Neurosci. 22 (11) (2005) 2917–2926.
[29] J.A. Coan, J.J. Allen, P.E. McKnight, A capability model of individual differences in frontal EEG asymmetry, Biol. Psychol. 72 (2) (2006) 198–207.
[30] A.J. Ellis, C. Kinzel, G.C. Salgari, S.K. Loo, Frontal alpha asymmetry predicts inhibitory processing in youth with attention deficit/hyperactivity disorder, Neuropsychologia 102 (2017) 45–51.
[31] J.S. Richman, J.R. Moorman, Physiological time-series analysis using approximate entropy and sample entropy, Am. J. Physiol.-Heart Circ. Physiol. 278 (6) (2000) H2039–H2049.
[32] F. Barwick, P. Arnett, S. Slobounov, EEG correlates of fatigue during administration of a neuropsychological test battery, Clin. Neurophysiol. 123 (2) (2012) 278–284.
[33] Y. Sun, J. Lim, K. Kwok, A. Bezerianos, Functional cortical connectivity analysis of mental fatigue unmasks hemispheric asymmetry and changes in small–world networks, Brain Cogn. 85 (2014) 220–230.
[34] Z. Yang, W. Jia, G. Liu, M. Sun, Quantifying mental arousal levels in daily living using additional heart rate, Biomed. Signal Process. Control 33 (2017) 368–378.
[35] A. Martínez-Rodrigo, R. Alcaraz, B. García-Martínez, R. Zangróniz, A. Fernández-Caballero, Non-lineal EEG modelling by using quadratic entropy for arousal level classification, in: Proceedings of the International Conference on Innovation in Medicine and Healthcare, Springer, Cham, 2016, June, pp. 3–13.
[36] E. Goldberg, The Executive Brain: Frontal Lobes and the Civilized Mind, Oxford University Press, Oxford, 2001.
[37] E.B. Bermudez, E.B. Klerman, C.A. Czeisler, D.A. Cohen, J.K. Wyatt, A.J. Phillips, Prediction of vigilant attention and cognitive performance using self-reported alertness, circadian phase, hours since awakening, and accumulated sleep loss, PLoS one 11 (3) (2016) e0151770.
[38] RM Yerkes, JD Dodson, The relation of strength of stimulus to rapidity of habit-formation, J. Comp. Neurol. Psychol. 18 (1908) 459–482.
[39] J.A. Taylor, Drive theory and manifest anxiety, Psychol. Bull. 53 (4) (1956) 303–320.
[40] M.J. McGinley, S.V. David, D.A. McCormick, Cortical membrane potential signature of optimal states for sensory signal detection, Neuron 87 (1) (2015) 179–192.
[41] G. Yang, Y. Lin, P. Bhattacharya, A driver fatigue recognition model based on information fusion and dynamic Bayesian network, Inf. Sci. 180 (10) (2010) 1942–1954.

Chin-Teng Lin received the M.S. and Ph.D. degrees in electrical engineering from Purdue University, West Lafayette, IN, USA, in 1989 and 1992, respectively. He is currently the Distinguished Professor of Faculty of Engineering and Information Technology, University of Technology Sydney, University Chair Professor of Electrical and Computer Engineering, NCTU, International Faculty of University of California at San-Diego (UCSD), and Honorary Professorship of University of Nottingham. Dr. Lin was elevated to be an IEEE Fellow for his contributions to biologically inspired information systems in 2005, and was elevated International Fuzzy Systems Association (IFSA) Fellow in 2012. Dr. Lin received the IEEE Fuzzy Systems Pioneer Awards in 2017. He was elected as the Editor-in-chief of IEEE Trans. on Fuzzy Systems in 2011–2016. He also served on the Board of Governors at IEEE Circuits and Systems (CAS) Society in 2005–2008, IEEE Systems, Man, Cybernetics (SMC) Society in 2003–2005, and IEEE Computational Intelligence Society (CIS) in 2008–2010. Dr. Lin is the Distinguished Lecturer of IEEE CIS Society from 2015–2017. He served as the Deputy Editor-in-Chief of IEEE Trans. on Circuits and Systems-II in 2006–2008. He has published more than 280 journal papers (Total Citation: 17,837, H-index: 61, i10-index: 216) in the areas of fuzzy systems, neural networks and cognitive neuroengineering, including approximately 130 IEEE journal papers.

Mauro Nascimben is currently working toward a M.S. degree at the Brain Research Centre, National Chiao Tung University (NCTU), Hsinchu, Taiwan. His current research interests include brain-computer interface and biomedical signal processing.

Jung-Tai King received the B.S. degree in psychology from National Cheng-Chi University in 1998, the M.S. degree in criminology from National Chung-Cheng University in 2001 and the Ph.D. degree in neuroscience from National Yang-Ming University (NCTU) in 2010. Currently, he is an assistant Research Fellow of Brain Research Center at NCTU, Taiwan. His research interests include psychophysiology, cognitive and social neuroscience and neuro-marketing.

Yu-Kai Wang received the B.S. degree in mathematics education from National Taichung University of Education, Taichung, Taiwan, in 2006, the M.S. degree in biomedical engineering from National Chiao Tung University (NCTU), Hsinchu Taiwan, in 2009, and the Ph.D. degree in computer science from NCTU, Hsinchu Taiwan, in 2015. He was a Visiting Scholar with the Swartz Center for Computational Neuroscience, University of California at San Diego, La Jolla, CA, USA, from 2013 to 2014. From 2016–2017, he was a postdoctoral researcher with the Centre for Artificial Intelligence in University of Technology Sydney, Australia. He is currently the Distinguished Professor of Faculty of Engineering and Information Technology, University of Technology Sydney. His current research interests include machine learning, computational neuroscience, biomedical signal processing, and the brain–computer interface.