A Worker's Fitness-For-Duty Classification and Prediction using Bio-signals

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1. Introduction

Fitness-For-Duty (FFD) refers to a worker's physical, physiological and psychological ability to competently and safely perform their tasks [1]. Implementing an effective FFD program provides reasonable assurance of human performance that workers do not pose a safety or security risk. The U.S. Nuclear Regulation Commission's (NRC's) regulation 10 CFR part 26, highlighted the importance of FFD programs in nuclear facilities [2].

To comply with the NRC regulation, nuclear industries implemented a drug & alcohol test and fatigue management (through reporting an employee's working hours) [3]. However, current FFD programs are limited in evaluating psychological distress. Detection comes with time delays and no reliable tools are available to measure actual fatigue. To address these limitations, this study proposed to develop a classification model for identifying potentially unfit for duty workers (Alcohol-use, Sleep-deprivation, High stress, Depression and anxiety) based on bio-signals.

2. Material & Method

A total of 124 subjects, from 20 to 29 years of age, participated in the experiments.114 subjects' bio-signals data were used for training a classification model and validating the model. After developing the model, 10 subjects whose there fitness status were blinded was also used to test fitness-status prediction. All subjects were in generally good health, took no medications, and had normal sleep habits. These subjects were categorized into Normal group (A: 36 subjects), Alcohol-use group (B: 21subjects), Sleep-deprived group (C: 11subjects), Heavy chronic stress group (D: 26 subjects), Depression group (E: 10 subjects), and Anxiety group (F: 10 subjects). The standards of classifying these groups are: 1) No caffeine, no smoking, no alcohol-use, no medications, and above 8 hours sleep; 2) above 0.03% Blood Alcohol Concentration (BAC); 3) less 1-2 hours of sleep over a 48 hours period; 4) above 26 stress scores of Depression Anxiety Stress Scales (DASS-21) [4] survey; 5) above 21 depression score of DASS-21; and 6) above 15 anxiety score of DASS-21.

Regardless of the type of sleep-deprived/alcohol-use/normal group manipulation used, the same protocol was applied for each visit. This study selected Electroencephalogram (EEG), Electrocardiogram (ECG), Galvanic Skin Response (GSR), Respiration, Blood Volume Pulse (BVP), and dynamic changes in blood pressure, the signal from the PPG sensor (BPHEG). The bio-signals were recorded in the resting states (Eye closed and Eye open). An EEG system with 19 channels (BrainMaster Discovery 24E^{TM} (Brain Master Technologies Inc.)) was used to record EEG data with Linked ears reference (LE). The Polygraph BiO device was also used to record ECG and other bio-signals from skin conductivity, respiration sensor and PPG sensor.

EEG frequency bands were categorized into the fourteen bands: 1) Delta: 1-4Hz; 2) Theta: 4-8Hz; 3) Alpha:8-12Hz; 4) Beta: 12-25 Hz; 5) High Beta: 25-30 Hz; 6) Gamma: 30~40Hz; 7) High Gamma:40~50 Hz, 8) Alpha1: 8-10Hz; 9) Alpha2: 10-12Hz; 10) Beta1: 12-15Hz; 11) Beta2: 15-18Hz; 12) Beta3: 18-25Hz; 13) Gamma1: 30-35Hz; and 14) Gamma2: 35-40Hz [5].

EEG raw data were subjected to a Fast Fourier Transform (FFT) algorithm to calculate the absolute (μV2) power and relative (%) power and the FFT Power Ratio (Arb). Absolute Power (AP) is the actual power (voltage) in a subject's EEG database (Power is microvolts squared). Relative Power (RP) is the relative power of each given band/sum of power from 1 to 50 Hz. FFT Power Ratio is calculated by one given band/ other given band.

For developing ECG indicators, RR (or NN) intervals (RRI or NN) were extracted from the ECG recordings during 2 min window. Typically two methods of analysis are reliable: time domain (beat-to-beat analysis) and frequency domain (calculating power spectrum density). The ECG frequency bands are categorized into Very Low Frequency (VLF: 0.0033-0.04 Hz), low frequency (LF: 0.04 - 0.15 Hz) and high frequency (HF: 0.15 - 0.4 Hz). From these two methods, ECG data can calculate 1) mean RR, 2) SDNN (standard deviation of NN intervals), 3) RMSSD (square root of the mean of the squares of the successive differences between adjacent NNs), 4) NN50 (the number of pairs of successive NNs that differ by more than 50 ms), 5) HF, 6) LF and 7)LF/HF.

Additionally, GSR, Respiration, BVP and BPHEG indicators were identified for measuring a worker's FFD status.

3. Results from Bio-signal Analysis

To categorize the differences in the six groups, this study performed the multivariate test of significance. Figures 1 and 2 show the differences between the mean values of possible EEG indicators depending on a subject's different FFD status. The significant indicator ($P^{**}<0.01$ and $P^{*}<0.05$) differences between the two groups were marked as**(blue box) and *(yellow box) in pairwise comparison table below the figures. From these results, 76 EEG indicators can define a subject's FFD status. These differences could be used to detect an NPP worker with an abnormal status.

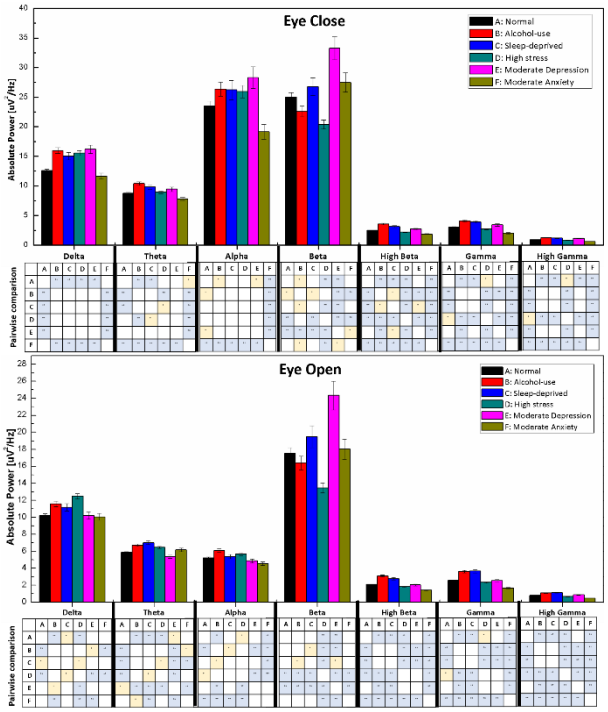

Figure 1. The Absolute Power differences of Six groups Group mean ($\pm S.E.$) Absolute Power difference (y-axis) between Six groups for Seven indicators (x-axis during Eye Closed and Eye Open.

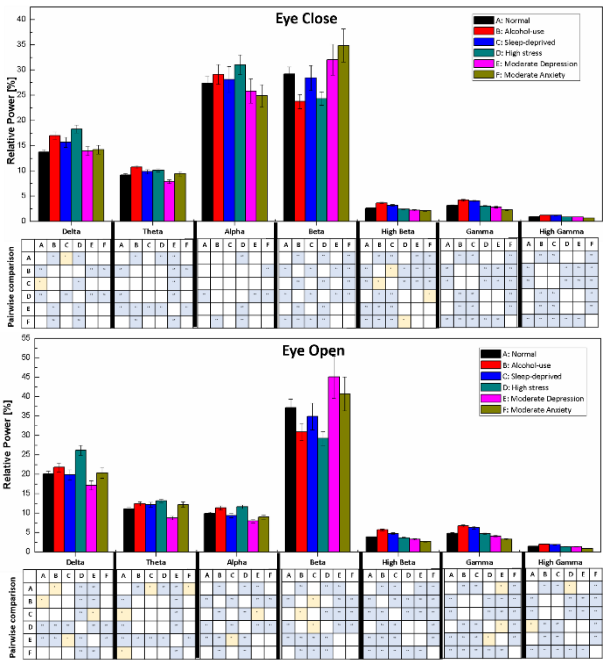

Figure 2. The Relative Power differences of Six groups Group mean ($\pm S.E.$) Relative Power difference (y-axis) between Six groups for Seven indicators (x-axis during Eye Closed and Eye Open.

In Alcohol-use group (B), the absolute and relative power of theta, alpha and high beta increased as shown in fig.1-2. These results were quite reliable based on previous studies. Higher absolute beta power of drunken people compared with those of healthy controls have consistently been reported [6-8]. Some researchers found that alcohol consumption has been associated with an increase in the production of EEG alpha activity [9-12], which is in association with euphoria [10]. In Table 1, alcohol-use group decreased HF and increased LF activity in comparison with normal group. In addition, SDNN value decreased and LF/HF increased similar to other studies [13-15]. Tsuji et al (1996) & Romanowicz et al. (2011) [16-17] reported acute alcohol consumption caused decreased parasympathetic (HF) and increased sympathetic LF activity.

Sleep-deprived subjects were found to have increased EEG absolute power in all frequency bands comparing with normal status. This result was similar to Corsi-Cabrera et al. (1992 & 1996) study [18-19]. In Table 1, the sleep-deprived group decreased LF and LF/HF indicators in comparison with the normal status. Previous researchers [20-21] also reported the same results.

Table 1. The result of comparison of significant ECG indicators depending on six groups during Eye Closed

	Normal		**Alcohol-use**		**Sleep-Deprived**	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Heart Rate [bpm]	72.12	0.33	102.03	0.47	71.41	0.82
SDNN [ms]	112.45	1.84	90.70	2.67	123.52	4.61
RMSSD [ms]	121.52	2.00	96.12	2.89	128.29	4.99
NN50	29.85	0.28	14.04	0.40	22.36	0.69
LF [ms2]	1868.17	48.70	1952.52	70.39	937.85	121.74
HF [ms2]	1648.05	30.72	1032.44	44.40	1002.76	76.80
LF/HF	1.72	0.06	3.56	0.09	1.38	0.15
	High Stress		**Depression**		**Anxiety**	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Heart Rate [bpm]	78.61	0.37	69.93	0.55	72.97	0.62
SDNN [ms]	134.92	2.07	93.35	3.09	147.82	3.48
RMSSD [ms]	138.95	2.23	98.06	3.35	159.39	3.77
NN50	24.81	0.31	23.94	0.46	20.81	0.52
LF [ms2]	1416.15	54.52	1367.40	81.68	1388.93	91.94
HF [ms2]	1146.53	34.40	1015.45	51.53	1018.18	58.00
LF/HF	1.74	0.07	1.07	0.10	0.89	0.11

Previous studies have not evaluated the clinical correlates of the EEG spectral profile in stress burden. Those with subjective stress burden was associated with increasing delta power and decreasing beta, high beta, gamma, and high gamma. Detecting stress is easier using

ECG rather than EEG since the ECG signal is a response from the autonomic nerve system similar to stress. Stressful people represented increased heart rate and decreased HF [22] as indicated in Table 1.

Compared with controls (normal group), depressive group evidenced greater overall relative beta power and absolute beta power [23]. During the resting eyes-closed EEGs, depressed subjects have shown elevated alpha and beta compared with controls [24]. In addition, delta and theta band activity has also been found to be increased [25-26]. Depressive symptoms were related to the decreased SDNN, RMSSD and HF [27-28]. The greater the severity of the symptoms, the greater the reduction in heart rate variability, and the Heart Rate Variability test may reflect the severity of the symptoms [27, 29].

In previous studies [30-31], both reduced EEG alpha activity and increased beta activity were thought to reflect increased cortical activation and have been associated with negative affect, such as anxiety. Our results showed the same result from the previous studies.

4. FFD Classification and Prediction using Machine Learning

This study identified 148 independent variables for the classification of FFD. These variables were calculated by frequency and time domain analysis. Dependent variable is a subjects' FFD status (A: Normal, B: Alcohol-use, C: Sleep-deprived, D: High/heavy stress, E: Moderate Depression, and F: Moderate Anxiety). Using these dataset, we trained a classification model.

Since our data set was not large, we used the 5-fold cross validation method by dividing the dataset into 5 groups. For each division, a model was trained by using out-of-fold observations (remaining 4 divisions excepting from selected fold) and this model's performance was evaluated by using in-fold data (Selected fold). The average test error was calculated over all folds. After selecting the validation method and training a model using MATLAB Machine learning toolbox, the overall accuracy of each classifier was evaluated. This accuracy includes the validation which estimates a model's performance on new data compared to the training data. This value is helpful to choose the best model. As indicated in Table 2, the classification accuracy was 98.9%~99.4%.

This study also calculated the prediction rate and validation accuracy. To verify the classification models' performance, this research collected ten new subjects without any information of physiological and psychological status. Based on the model, we got y-fitting value which means the predicted value. After the blind test, the self-evaluation measurements were performed by another experimenter compared with EEG collection experimenter. These data were used for comparing the prediction value from our suggested algorithm with collected actual value. The prediction rate was 76.8% using the SVM and 96.32% using the Ensemble Bagged Tress method. The validation accuracy based on new test set was almost 100%. This implies our classification model's performance is good.

Table.2. Classification and Prediction results

Model	**Classification Accuracies**	**Validation accuracy** (new test)	**Prediction rate**
Cubic SVM	98.9%	95.26%	76.84%
Fine KNN	97.8%	100%	65.26%
Ensemble Bagged Trees	99.4%	100%	96.32%

5. Conclusion

This research investigated the feasibility of classifying a worker's FFD by using power spectrum analysis on bio-signals data. The analyses were based on the measurements on independent variables (76 EEG indicators, 64 ECG indicators, 2 BVP, 2 GSR, 2 Respiration and 2 BPHEG) and dependent variable (subject's fitness status: normal, alcohol-use, sleep-deprived, heavy stress, moderate depression and anxiety) using MANOVA. The results showed the resting states (Eye closed and Eye Open) for bio-signal indicators have a statistically significant difference for at-risk students compared to healthy college students. The performance of the newly developed classification models were also judged to be reliable when identifying worker's fitness status. These results can be applied directly to FFD monitoring systems of nuclear power plants as well as other high reliability fields, such as aerospace, military and transportation.

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