HRV-Based Operator Fatigue Analysis and Classification Using Wearable Sensors

Hilal Al-Libawy, Ali Al-Ataby, Waleed Al-Nuaimy, Majid A. Al-Taee
Department of Electrical Engineering and Electronics
University of Liverpool, Liverpool, UK
e-mail: {abbood, aliataby, wax, altaeem}@liverpool.ac.uk

Abstract—**Fatigue assessment and quantification are essential requirements to reduce the risks that occur as a consequence of a fatigued operator. The new wearable device technology offers an accurate measuring ability to one or more of fatigue-related biological data, which helps in quantifying fatigue levels in real-life environments. This paper presents a new heart rate variability (HRV) based operator-fatigue analysis and classification method using low-cost wearable devices. HRV that is considered a robust fatigue metric is measured by several wearable devices including a chest-strap heart monitor and a wrist watch that measures heart rate, skin temperature and skin conductivity. The data collected from real subjects are used to create a training dataset for fatigue analysis and classification. Two supervised machine-learning algorithms based on multi-layer neural network and support vector machine are developed and implemented to identify the alertness/fatigue states of the operator. Performance of the developed classifiers demonstrated high alertness/fatigue prediction accuracy. Such findings proved that the proposed analysis and classification method is valid and practically applicable.**

Keywords—alertness; heart rate variability; neural networks; operator fatigue; support vector machine; wearable sensors.

I. Introduction

Fatigue is a mental state and usually combined with slower response times. The circadian rhythm and sleep deprivation are the drives of this natural state. The importance of research in mental fatigue problem is the fatal errors come from operators and drivers which may lead to dangerous consequences [1]. Air transportation is one of the fields that is thoroughly covered for risk assessment; including fatigue and sleepiness as main risk factors [2]. Although some studies suggest that aviation transportation is the safest form of transportation, human errors remain the main cause of accidents [3].

Different approaches and methods have been reported in literature to study the driver fatigue. Most of these approaches were using biological laboratory data, which was collected by relatively expensive medical equipment. Various classification algorithms, including Artificial Neural Network (ANN), Support Vector Machine (SVM), K-nearest Neighbour (KNN), Decision Tree (DT), Naïve Bayes (NB) and others, have been adopted in fatigue [4] – [6], medical diagnosis [7] – [9], therapy of chronic diseases [10] and other applications. However, performance of these classifying algorithms can vary from one application to another [11].

In [12], the authors utilized the fluctuation in heart rate for fatigue monitoring. The heart rate volatility that was obtained by historical data of heart rate fluctuation, however, is not heart rate variability but related to it. The relationship between frequency power ranges is described in [13] where it was reported that the ratio of low to high frequency components decreases with fatigue evolution.

The Activity of the autonomic nervous system (ANS) that is addressed as a trusted source of information has two components; sympathetic nervous system (SNS) and parasympathetic nervous system (PSNS) [6]. The interaction between these two components is reflected in some biological signs such as core temperature, skin conductivity and heart rate. Heart rate variability (HRV) is affected clearly with activity of ANS components that are changed with sleep/wake activity [14] - [17]. Recent technology developments have led to design and development of low-cost wearable devices that are capable of accurately measuring and collecting various biological data [18], [19] including the HRV. Consequently, measuring the operator fatigue through these devices becomes quite feasible at an affordable cost.

Benefiting from the findings previously reported by the authors in [1], [20] as well as the newly developed wearable biosensors, this paper presents a new heart rate variability (HRV) based operator-fatigue analysis and classification method using low-cost wearable devices. A dataset is created from data

This research was supported by a PhD fellowship from Babylon University- Ministry of Higher Education and Scientific Research, Iraq; Grant No. MOHESR-IQ-2013-1257. The authors would also like to thank FMI Ltd., UK for their support in providing experimental data for the bio-signals used in this study.

978-1-5090-1291-6/16/$31.00

collected from real subjects and used for the proposed fatigue analysis and classification. The results obtained from ANN and SVM classifiers demonstrated high alertness/fatigue prediction accuracy.

The remainder of this paper is organized as follows. Section II overviews the most common metrics of HRV. Section III describes the experiment classification approaches are presented in Section IV. The obtained fatigue classification results and their correlation to HRV are presented and discussed in Section V. Finally, the work is concluded in Section VI.

II. Heart rate Variability

The duration between two heartbeats that is called normal-to-normal interval (NN) [21] typically can be measured from two adjacent QRS complexes that are captured from ECG signal. Sometimes, this duration is also termed as R-to-R (RR) interval [22]. Fig. 1 shows ECG signal captured from one of the participants with some details about QRS complex and RR intervals. The variation in RR intervals that represents the heart-rate variability (HRV) is a non-intrusive and can be practically used to measure the sympathetic and parasympathetic modulation in humans [23]. The HRV metrics are calculated from these NN periods that reflect the variation between heartbeats intervals. An example of a 10-minute HRV pattern for one of the participants involved in this study is shown in Fig. 2.

To calculate the HRV from ECG, it was suggested in [24] that at least 5-minute measurement period should be considered. HRV metrics can generally be categorized into five domains: time, frequency, complexity, fractal and nonlinear [25]. Table I summarizes the metrics of common use in the time and frequency domains. In the present study, an average record duration of 10 minutes is considered adequate to obtain reasonably accurate and reliable results. The HRV metrics adopted in this work are calculated with the aid of HRVAS software application that is reported in [26], [27].

	Metric	Description
Time domain	SDNN	Standard Deviation of NN intervals
	RMSSD	Root Mean Square of Successive Differences
	NN50	Number of pairs of successive NNs that differ by > 50 ms
Frequency domain	VLF	Very Low Frequency power from 0.0033 - 0.04 Hz
	LF	Low Frequency power from 0.04- 0.15 Hz
	HF	High Frequency power from 0.15 - 0.4 Hz
	LF/HF	Ratio of Low Frequency power to High Frequency power

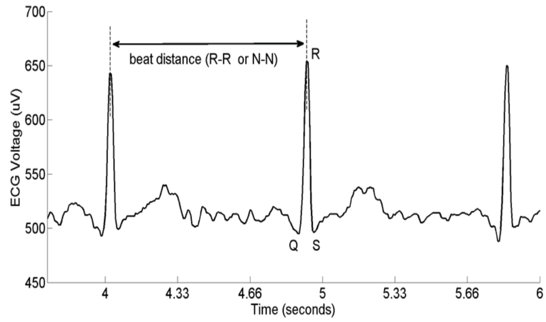


Fig. 1. Example of ECG signal with QRS complex

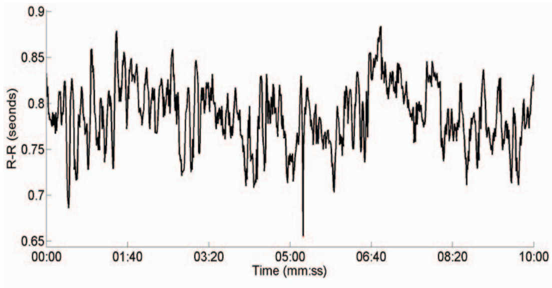


Fig. 2. R-R intervals extracted from heart-rate monitor

III. Materials and methods

A. Study Subjects and Bio-Data

A total of 6 volunteers, aged 16 - 50 years with biomass index of 24-35 were participated in this study.

A fitness watch, shown in Fig. 3, that is capable of saving bio-data in its internal memory is adopted in this study. It is used to collect several bio-data, including heart rate, body temperature, and skin conductance, from the participants. HRV is obtained from ECG signal. Through calculating the heartbeat spacing (R-R spacing), as illustrated in Fig. 1, the R-R period is measured by heart-rate sensor strap (Polar H7) shown in Fig. 4. This device is equipped with a Bluetooth and thus capable of sending the collected data wirelessly to handheld devices (e.g. smartphones and tablets).

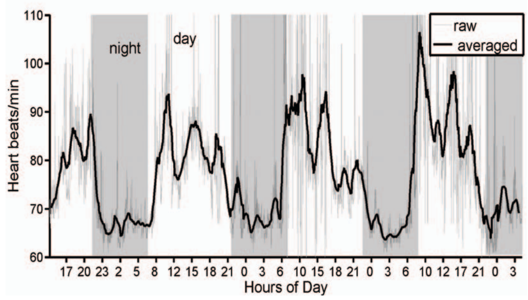
B. Dataset

The experiment is conducted for a period of 30 days using smart watches around the day. Each participant was asked to synchronize his data in daily manner and upload it to the cloud using his mobile phone with installed companied application of the watch. The data was stream of samples with resolution of a sample per minute for each type of data. Then the data was pre-processed and filtered using windowed low pass filter with 30-sample window size.

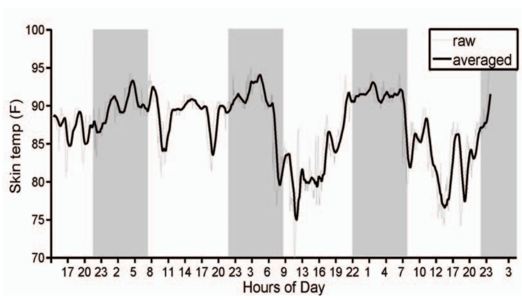
Fig. 3. Example of a fitness tracker watches showing heart rate and calories burnt [28]

Fig. 4. Example of a fitness heart-rate sensor strap, (Polar H7) [29]

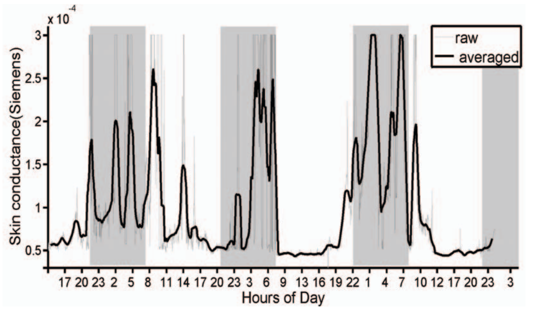
1) Input-data vector: The collected data from tracking watch was pre-processed and analysed to generate statistical metrics like 30 minutes windowed mean (shown in Fig. 5) and standard deviation also a frequency domain analysis was conducted to generate the power spectral density and calculate the three bands of power frequency. Finally, six features were selected as an input-data vector. Fig. 5 illustrates clearly the correlation between day-night changes in recorded bio-data that are used to generate fatigue-related features [20].



(a) Heart rate data



(b) Wrist temperature data

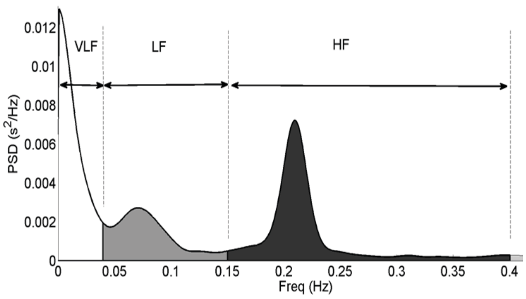


(c). Skin conductance data

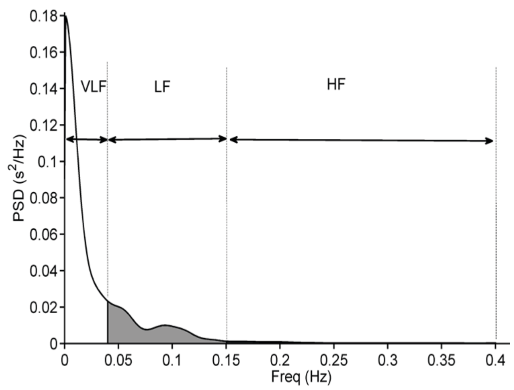
Fig. 5. Examples of the collected bio-signals that are used for features generation

2) Output-data vector: HRV, which can be considered a highly correlated fatigue metric, is derived from chest strap heart monitor based on this monitor measures. Another set of biological data is collected from wrist sensor such as heart rate, skin temp and skin conductivity. One of HRV metric (LF/HF) was chosen to label the output-data vector in two states (alert and fatigued). The LF/HF showed very clear correlation of fatigue level between day and night.

Fig. 6 shows two examples of Power Spectral Density (PSD) in which it can be noticed that the ratio of LF/HF increases in the midday while decreases at late night. This fatigue-correlated change in LF/HF metric is used in this work and labelled as two classification states as alert and fatigued participant.



(a) PSD example at 23:15 (fatigued)



(b) PSD example at 14:15 (alert)

Fig. 6. Example record of power spectral density for HRV

PSD is measured using many methods and analysis approaches and in this work three methods are implemented and they are: Welch, Burg and Lomb-Scargle methods [30].

The data is collected around 16 hours daily using fitness heart rate sensor strap Polar H7 [29] in companion with smartphone application to collect and record data from sensors and upload it to data visualization framework website Fluxtream [31]. The R-R data is then analysed and HRV metrics are generated. As expected, LF/HF metric is tend to be of a clear correlation with growth of fatigue at night and this metric is chosen to represent the output data.

Fig. 7 demonstrates an example of the calculated LF/HF metric around wakening hours which shows the growth of this metric from early morning to reach its maximum at afternoon then it decays at the end of day. In spite of that the three methods of PSD methods of calculations show the alertness pattern, Welch and Burg methods tend to coincide all times.

C. *Preprocessing*

The missing data or out of range data problems are common problems with data collecting from sensors. This problem may come from sensor not-reading slots or may the participant did not wear the watch or the chest strap for many reasons like charging time or shower time.to overcome this problem some approaches are followed. The first deals with slots less than 60 sample by interpolate the missing data, while the second way was used when data-missing slot was greater than 60 samples using unequally space frequency domain analysis.

IV. Alert-Fatigue Classifier

Based on LF/HF measures that are calculated from R-R data, smoothing and interpolation fitting is implemented over data to produce the output vector of the classifier. Fig. 8 shows an example of LF/HF changing around day hours for one participant. The three curves showing in this figure represent the three method of PSD calculation (Welch, Burg and Lomb-Scargle). Welch approach is chosen to create the output data vector because it mostly correlates with input vector. Dynamic threshold, which depending on individual differences, is chosen to label the output vector into alert and fatigued states. The threshold level is chosen based on performance output of the classifier. HRV and bio-data set are combined to create training set and use it with supervised machine learning algorithms to build fatigue classifier.

Fig. 9 shows a block diagram of the proposed classifier. Three types of data (hear rate, wrist temperature and skin conductance) are collected from fitness track watch and pre-processed to get reliable set of data. After that, feature extractor step is carried out to produce around 14 time and frequency domain features. Only six out of total features was selected because of their good impact on classification results. The chosen features are:

- Heart rate 30 sample windowed mean.
- Heart rate standard deviation.
- Wrist temperature 30 sample windowed mean.
- Wrist temperature standard deviation.
- Heart rate PSD (total power of 30 samples).
- Wrist temperature PSD (total power of 30 samples).

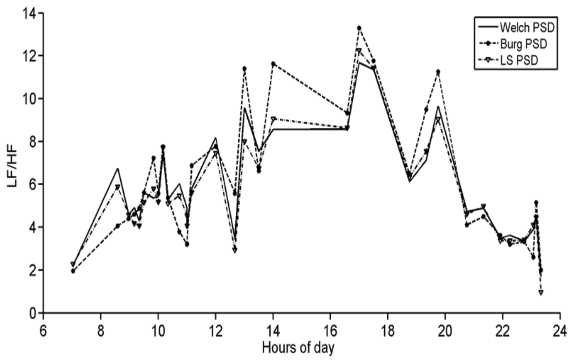


Fig. 7. Example of HRV metric (LF/HF PSD) for one participant calculated in three methods (Welch, Burg and Lomb-Scargle)

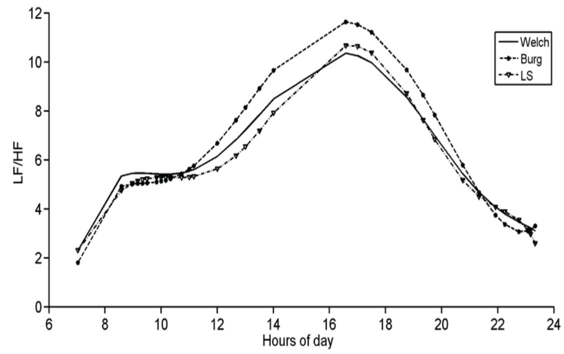


Fig. 8. Example Polynomial fitting of HRV metric (LF/HF PSD) for one participant calculated in three methods (Welch, Burg and Lomb-Scargle)

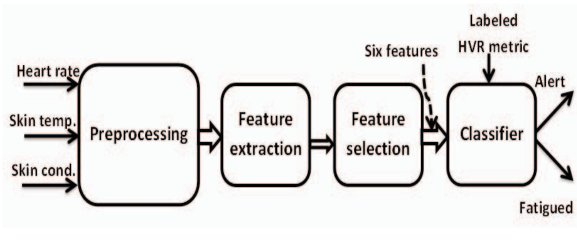


Fig. 9. A block diagram for the fatigue-alert classifier

The classification phase is implemented using input-output dataset to classify the operators into alert state and fatigue states.

A. Artificial Neural Network

ANN is built and trained with three sets on 80% of the available dataset while the rest 20% records is used for test phase. The proposed ANN is elaborated with feed-forward ANN based on six nodes input layer and one hidden layer layers and one single output unit with a tangent-sigmoid transfer function. Moreover, many configurations were considered to identify the ANN structure with the best performance. This involved changing the numbers of hidden layer and the nodes in each layer as well as changing in training algorithms and decision transfer function. Levenberg-Marquardt back-propagation algorithm was chosen for the ANN training.

B. Support Vector Machine

One of the well-known classification approaches is the SVM. Based on set of training data, SVM can generate a model that can classify untrained data. This work is used SVM to classify the collected set of data in to two classes (alert and fatigued). Two states are identified, alert and fatigued states, and the features of each are normalised. The classification phase is implemented using input-output dataset to classify the operators into alert state and fatigue states.

V. RESULTS

Eight trials of randomly selected records from validation, training and testing sets were conducted to calculate the accuracy of classification for both classifiers. Table II shows the classification accuracy for ANN and SVM with including two output states. SVM approach shows advantage of accuracy scores over ANN approach.

TABLE I. CLASSIFIER ACCURACY

Output states	ANN	SVM
Alert	94.7%	97.2%
Fatigued	88.3%	91.3%

VI. CONCLUSIONS

Results show the ability of using low-cost wearable devices to measure, quantify, classify and validate fatigue status of operators in real-life environments. The proposed classifier is successfully implemented with acceptable accuracy. HRV extraction from collected R-R data is used to quantify fatigue level in accurate approach after tackling artifacts and noisy data. The labeling process is implemented by choosing different threshold levels that reflects the individuality of operators. The obtained results demonstrated clearly that the SVM classifier is more accurate than the ANN and therefore, it can be considered as a promising tool for online fatigue detection based on measurable bio-data (i.e. heart rate or skin temperature).

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