Multisensor Data Fusion in Fatigue Detection Using Wearable Devices

Hilal Al-Libawy, Ali Al-Ataby, Waleed Al-Nuaimy, Majid A. Al-Taee

Abstract: Operator performance and safety that are both affected by the operator mental status (fatigue/alert) are basic requirements in work environments. The needs for practical and low-cost approaches for fatigue detection are therefore required by governmental, industrial and safety organizations. This paper proposes a new approach for operator fatigue detection that is based on biological data collection using accurate, low-cost and easy to use wearable devices. Three bio-data sensors for heart rate, wrist temperature and skin conductivity are adopted in this work for data collection and generation of fatigue-related metrics. Effective features of the collected bio-data are identified and labeled using the heart-rate variability metric that is measured by a wearable chest-strap heart monitor. The data collected from real subjects is used to train a dataset for fatigue analysis and classification using sub-classifiers based on artificial neural networks . Decision-level data fusion technique based on Bayesian combiner is then applied to enhance the accuracy and confidence of the obtained classification results. Performance of the developed alertness/fatigue detector is assessed experimentally and the obtained findings demonstrated acceptable performance in terms of modularity, accuracy, sensitivity and specificity when compared to individual classifiers.

Keywords: alertness; artificial neural networks; heart-rate variability; operator fatigue; Bayesian fusion; wearable sensors

1 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 that come from operators and drivers that may lead to dangerous consequences [1]. For example, 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

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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 operator fatigue. Most of these approaches were using biological laboratory data collected by relatively expensive medical equipment. Numerous machine learning and classification algorithms such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), K-nearest Neighbour (KNN) and others have also been proposed and used in a wide range of applications including fatigue detection [4, 5, 6], medical diagnosis [7, 8, 9], decision support and therapy of chronic diseases [10] and other applications. However, performance of these algorithms can vary from one application to another [11]. In [12], the fluctuation in heart rate was utilized for fatigue detection and monitoring. The heart rate volatility that does not represent the heart-rate variability (HRV) but relevant to it was obtained from historical data of the heart rate fluctuation. The relationship between frequency power ranges of HRV in the frequency domain components was reported in [13]. It was described that the ratio of low to high frequency components is inversely proportional with fatigue evolution (i.e. high ratio for low fatigue level and vice versa).

Biological explanation of the HRV behaviour is based on the fact that the activity of the autonomic nervous system which is addressed as a trusted source of information. It has two main components; sympathetic nervous system and parasympathetic nervous system [5]. The interaction between those two components is reflected in some biological signs; of these, the heart rate, core temperature and skin conductivity are the most important. The HRV is significantly affected by the activity of the autonomic nervous system components that are in turn vary with sleep/wake activity [14, 15, 16, 17].

Recent technology advancements have led to design and development of numerous low-cost wearable devices [18, 19, 20] capable of accurately measuring and collecting various biological data, including the HRV. Utilization of these devices in fatigue-related studies has become affordable and quite feasible over the past five years. Benefiting from these technology advances in wearable biosensors, this paper builds on and extends the work reported by the authors in [21]. It proposes a new approach for operator fatigue detection that is based on biological data collection using accurate, low-cost and easy to use wearable devices. A decision-level data fusion technique based on Bayesian filter is suggested to enhance the accuracy and confidence of the obtained classification results. Performance of the developed fatigue detector can therefore be favourable compared to the state of the art findings.

The rest of this paper is organized as follows. Section 2 overviews common metrics of the HRV, focusing on the ratio of low/high frequencies of the heart rate changes that are of a particular interest in this study and gives theoretical background of Bayesian theorem. Section 3 presents the materials and method of this study with a particular focus on implementation of the proposed fatigue detection approach. The obtained results are presented and discussed in Section 4. Finally, the work is concluded in Section 5.

2 Background

2.1 Heart rate variability

Heart-rate variability (HRV) can be defined with the aid of Fig. 1 as follows. The duration between two heartbeats (also called normal-to-normal interval, NN) is typically measured from two adjacent QRS complexes that are captured from the ECG signal [22]. It should be mentioned here that the RR and NN terms are interchangeably used in literature and clinical practice [23]. Figure 1 shows an example of an ECG signal with some details about QRS complex and RR intervals. The variation in RR intervals that represents the HRV is characterized as a non-intrusive technique. It can be practically used to measure the sympathetic and parasympathetic modulation in humans [24].

HRV metrics that are calculated from the RR periods that reflect the variation between heartbeats intervals can be categorized into five domains: time, frequency, complexity, fractal and nonlinear [25]. A measurement period of at least 5 minutes is considered to calculate the HRV from ECG, as suggested in [26]. Table 1 summarizes the metrics of common use in the time and frequency domains. Of these, the LF/HF is considered of a particular importance in this study.

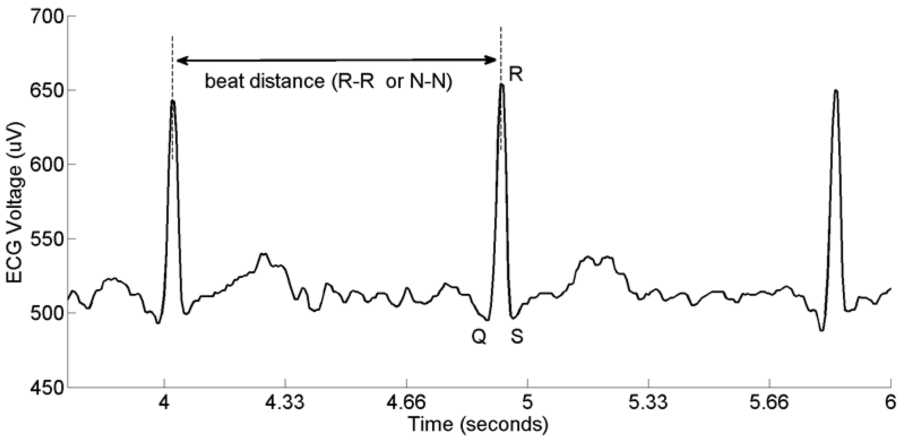


Fig. 1. Example of ECG signal with QRS complex.

Table 1. HRV Metrics.

Domain	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 to high frequency power

2.2 Bayesian data fusion

Several definitions for data fusion have been reported in literature. However, the mostly agreed upon definition is [27], *"Information fusion is the synergistic integration of information from different sources about the behaviour of a particular system, to support decisions and actions relating to the system."*

In this study, a dataset is created through collecting data from volunteer participants through several bio-data sensors (i.e. heart rate, wrist temperature and skin conductivity). As the raw data collected from these sensors cannot be merged directly, a data fusion technique is proposed and implemented to improve overall performance of the proposed fatigue detector. Generally, data/information fusion approaches can be divided into three levels [27]; (i) a data-level that combines multisensor raw data, (ii) feature-level that merges features extracted from raw data, and (iii) a decision-level. The latter approach is adopted in this study, using a Bayesian algorithm [28, 29] to improve accuracy and confidence of the data classification stage.

Bayesian theorem relates probabilities of two events, depending on posterior knowledge. The joint probability of the two events F (one of two classes), C (one of three classifier) can be mathematically described as (F, C), while the conditional probability of F occurring given that C has already occurred can be written as (F | C). Mathematically, Bayes' rule relates these probabilities as

$$(F, C) = (F \mid C)\,(C) \tag{1}$$

$$(F \mid C) = \frac{(C \mid F)\,(F)}{(C)} \tag{2}$$

If there are several events F_i, then event F can be written as normalization of mutually exclusive events as

$$(F \mid C) = \frac{(C \mid F)\,(F)}{\sum_i (C \mid F_i)\,(F_i)} \tag{3}$$

The term $(C_i \mid F_i)$ can be calculated from individual ANN classifier outputs as prior probabilities [30] and the classifier confidence can be approximated as a posterior probability [31]. Taking into account these assumptions, Bayesian fusion can be implemented to enhance the overall classifier performance post the fusion process.

3 Materials and Method

A total of 9 male volunteers, aged 16 - 50 years with body mass indexes of 21-35 were participated in this study. Each participant is provided with two wearable devices; a fitness tracker watch (shown in Fig. 2a) and a heart-rate sensor strap (Polar H7, shown in Fig. 2b). The fitness tracker watch 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. The participant's data was collected at a rate of 1 reading per minute.

(a) Fitness tracker watches [32].

(b) Fitness heart-rate sensor[33].

Fig. 2. Examples of a fitness wearable devices.

The HRV is obtained from the RR period is measured by heart-rate sensor strap that is equipped with a Bluetooth communication facility. The measured data can therefore be wirelessly transmitted in real time to a wide variety of handheld devices (e.g. smartphones and tablets). The data is collected around 16 hours daily using the fitness heart-rate sensor strap in companion with a smartphone application to collect and record data from sensors and then upload it to a remote website, Fluxtream [34].

The method of this study comprises three distinct stages; (i) pre-processing, (ii) feature extraction and labelling and (iii) fatigue detection. These stages are shown in the block diagram of Fig. 3 and are described as follows.

3.1 Pre-processing and HRV calculation

3.1.1 Pre-processing

Missing and out of range data are common problems in data collection; it can be caused by a sensor or a human failure. For example, a participant inability of wearing the watch or the chest strap during battery charging or shower time. To mitigate the impact of this problem, some practical arrangements are considered; (i) dealing with slots of less than 30 samples through interpolating the missing data and (ii) using unequally space frequency domain analysis when data-missing slot was greater than 30 samples.

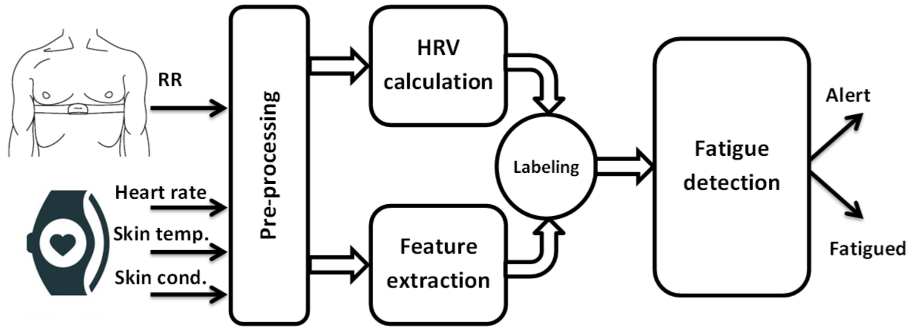
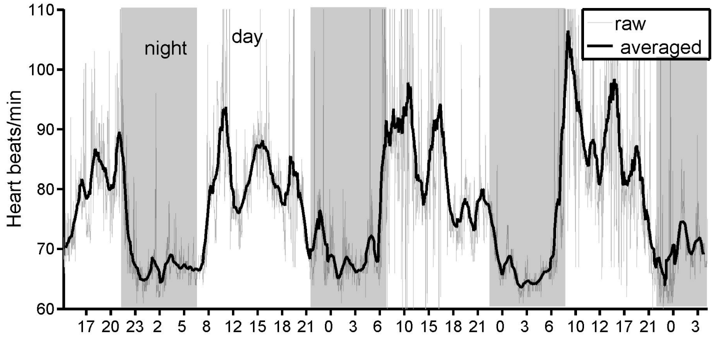


Fig. 3. Block diagram for the proposed system.

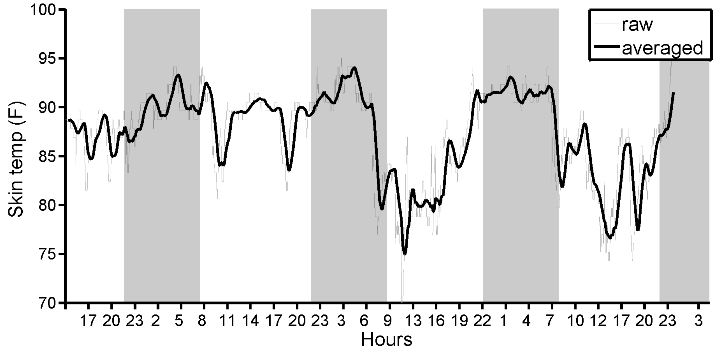
The collected data from tracking watch was pre-processed and analysed to generate statistical metrics like 30-min windowed mean (shown in Fig. 4) and standard deviation also a frequency domain analysis was conducted to generate the power spectral density and calculate the three bands of power frequency. Finally, a set of several features were selected as an input-data vector. The selected set of features are discussed later in Section 3.2.

3.1.2 HRV measurement

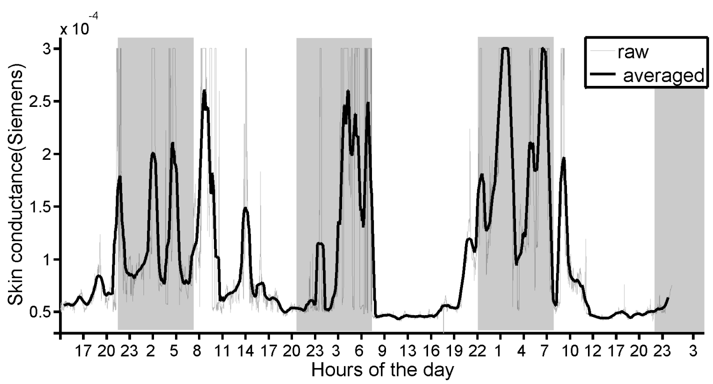
An example of 10-minute RR intervals for one of the participants involved in this study is shown in Fig. 5. The collected RR data from chest strap is analysed and used to generate HRV. An average record duration of 10 mins is considered adequate to obtain reasonably accurate and reliable HRV metrics. Theses metrics are calculated with the aid of an existing HRVAS application reported in [35, 36].



(a) Heart-rate data



(b) Wrist-temperature data



(c) Skin-conductance data

Fig. 4. Examples of the collected bio-signals

Power Spectral Density (PSD) is usually calculated using many methods and analysis approaches. In this work, three methods are adopted [35, 37]; Welch, Burg

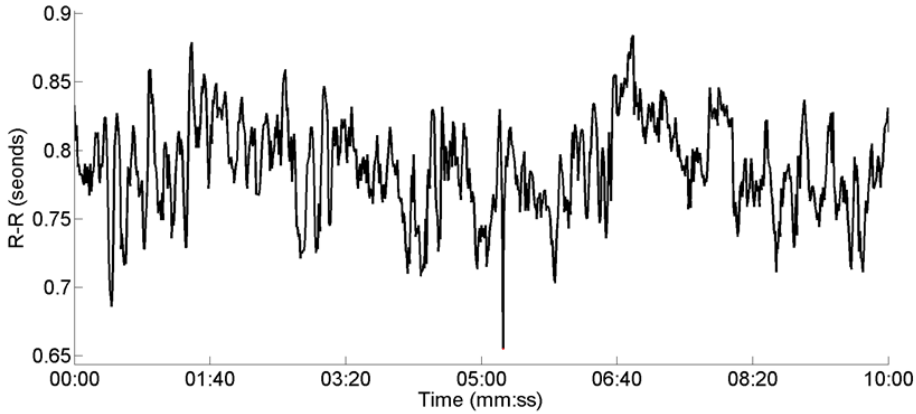


Fig. 5. RR intervals extracted from heart-rate monitor.

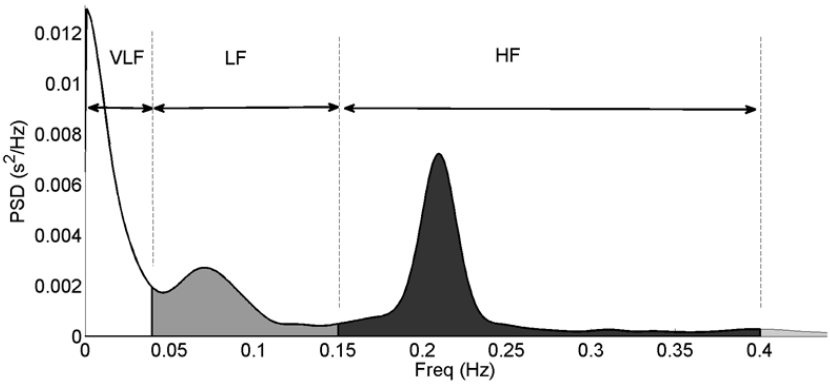
and Lomb-Scargle. Figure 6 shows two examples of PSD in which we can notice that the ratio of LF/HF increases in the midday while decreases at late night. This fatigue-correlated change in LF/HF metric is used in this work and labelled as two classification states as alert and fatigued participant.

As expected, LF/HF metric shows a trend of a clear correlation with growth of fatigue at night and this metric is chosen to represent the output data. Figure 7 shows an example of one participant calculated using the above-mentioned methods. The calculated LF/HF metric around the wakening hours which demonstrates the growth of this metric from early morning, reaching its maximum at afternoon, and then decaying at the end of day. Despite that the three PSD calculations methods show the alertness pattern, Welch and Burg methods tend to coincide all the times.

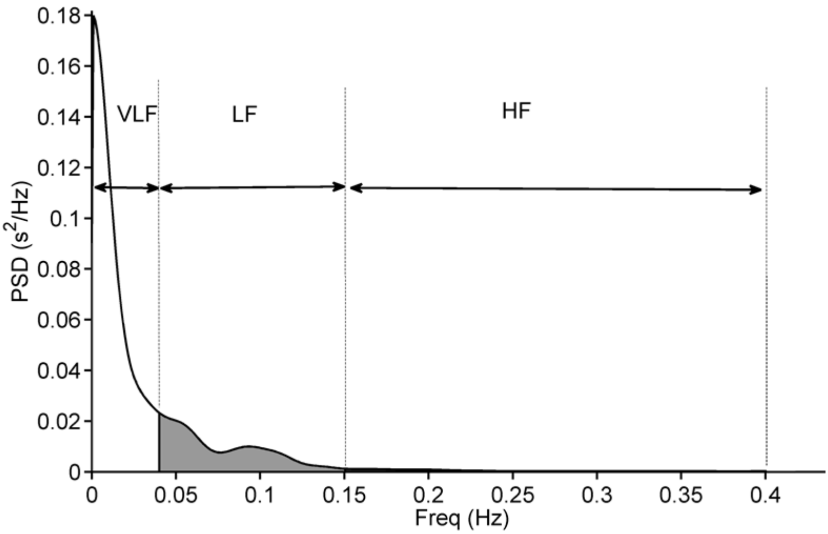
3.2 Feature extraction and data labelling

The collected data from the fitness watch (hear rate, wrist temperature and skin conductance) are passed to feature extraction stage after pre-processing stage. After feature extraction, the following 6 out of 14 features are chosen to be the most effective:

- Heart rate 30 sample windowed mean
- Heart rate standard deviation
- Wrist temperature 30 sample windowed mean
- Wrist temperature standard deviation
- Skin conductance 30-sample windowed mean
- Skin conductance standard deviation



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



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

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

Based on LF/HF measures that are calculated from RR data, smoothing and interpolation fitting is implemented over data to produce the output vector of the classifier. Figure 8 shows an example of a polynomial fitted HRV metric (LF/HF) for one participant calculated in three methods (Welch, Burg and Lomb-Scargle).

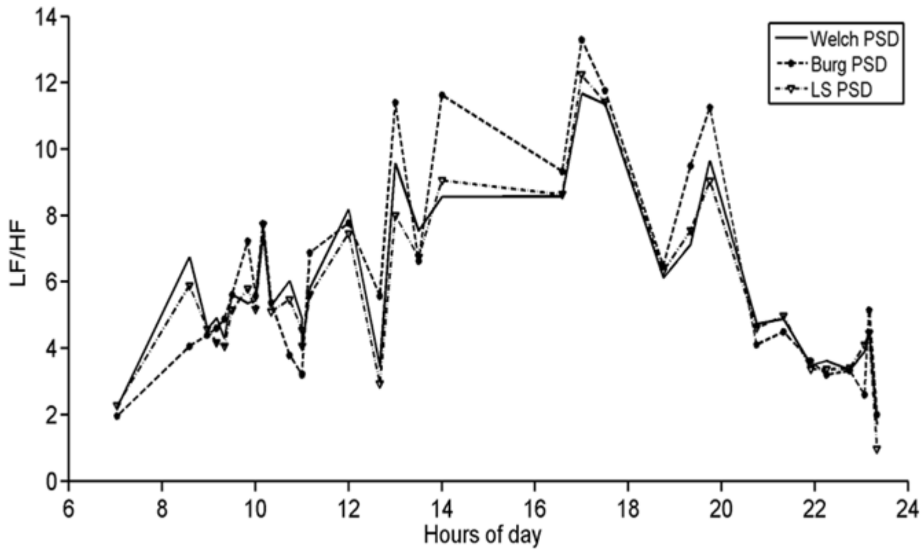


Fig. 7. Example of HRV metric, LF/HF PSD.

The three curves showing in this figure represent the three method of PSD calculation (Welch, Burg and Lomb-Scargle).

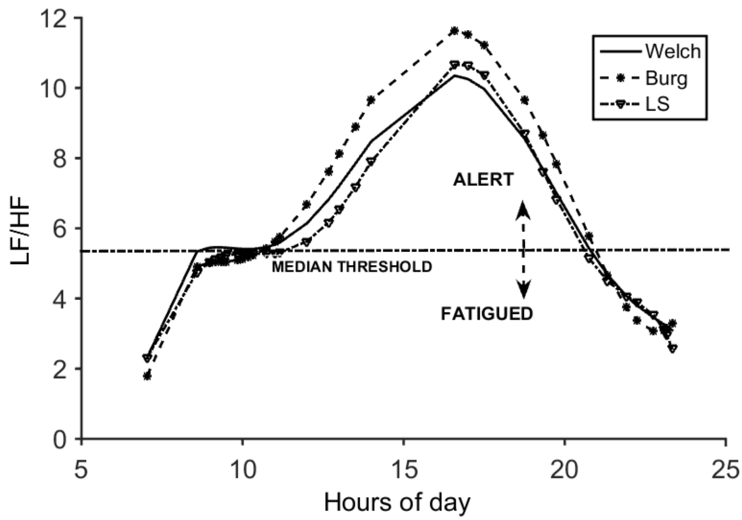


Fig. 8. Example of a polynomial fitted HRV metric, the LF/HF.

Among the PSD methods mentioned above,the Welch method was selected in this study. This was mainly because it is producing the highest correlation coefficient between the HRV fitting polynomial and pre-processed data. Dynamic threshold, which is depending on individual differences, is chosen to label the output vector into alert and fatigued states. The median metric of HRV data over the day is chosen as threshold level. This threshold is used to label the bio-data set with two labels, alert label for the part above the threshold line and fatigued for the part below the threshold line. The bio-data set are combined with its labels to create training set and use it with supervised machine learning algorithms to build fatigue classifier.

3.3 Fatigue detection

This stage proceeds in two steps; classification and fusion. The labelled features are fed to detection stage which in turn generates decision on the operator fatigue status (i.e. alert or fatigued). Figure 9 shows ablock diagram for the proposed tow-steps detector, starting from three sub-classifiers and ending with Bayesian fusion stage.

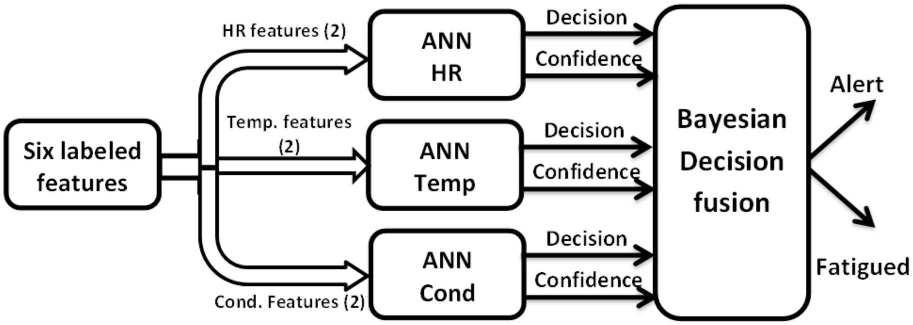


Fig. 9. Two-stage fatigue detector (classifier and fuser).

3.3.1 Classification

The collected dataset is used to classify the operator status into alert and fatigue states. The dataset is divided into three subsets; each subset is selected based on data type (heart rate, wrist temperature and skin conductance). Three ANN classifiers are then trained by 70% of individual feature subset, while the rest 30% are used for test.The structure of the ANNs is based on the feed-forward with an input layer, a hidden layer and two output units with a tangent-sigmoid transfer function.

3.3.2 Bayesian Fusion

At this stage, the final decision are generate using the decision and confidence values received from the ANNs. As shown in Fig. 9, the output of each classifier is approximated as posteriors probability. Bayesian fusion algorithm then combine the output of the sub-classifiers by applying maximum a posteriori probability (MAP) rule [38, 39]. The detection results post fusion stage are shown in Table 2 . As illustrated, the overall classification accuracy, sensitivity and specificity are improved when compared to the results obtained from the sub-classifiers.

4 Results and Discussion

Numerous experiments have been carried out over a period of 9 weeks; (each experiment takes about a week to complete). The participants were instructed to collect and synchronize data with a remote server on daily bases. A user-friendly data collection and management application was deployed and used on the handheld device for this purpose.

Different configurations were also considered to identify the ANN structure with the best performance. These configurations involved changing the number of hidden layers and associated nodes as well as optimizing the training algorithm and the decision transfer function. Levenberg-Marquardt back-propagation algorithm was eventually selected for the ANNs' training. Figure 10 shows an example of the sub-classifiers performance in terms of two metrics; (i) confusion matrix and (ii) receiver operating characteristics.

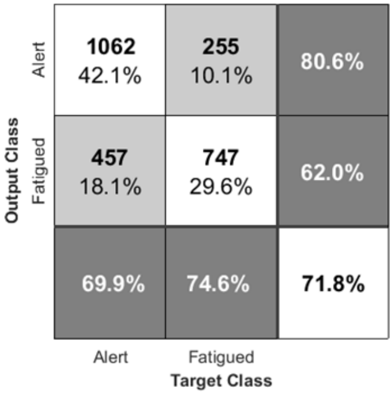
Several trials of randomly selected records from data sets were conducted to calculate the accuracy of classification for all classifiers. Table 2 clearly shows the superiority of the Bayesian fuser results over the individual sub-classifiers in terms of accuracy and specificity. This trend of findings is also expected to be valid for most classifiers when they fed with larger set of effective features. The sub-classifiers demonstrated close results in terms of accuracy. The heart rate sub-classifier demonstrated the highest accuracy (71.8%), while the skin conductance sub-classifiers demonstrated the least accuracy (62.2%).

5 Conclusions

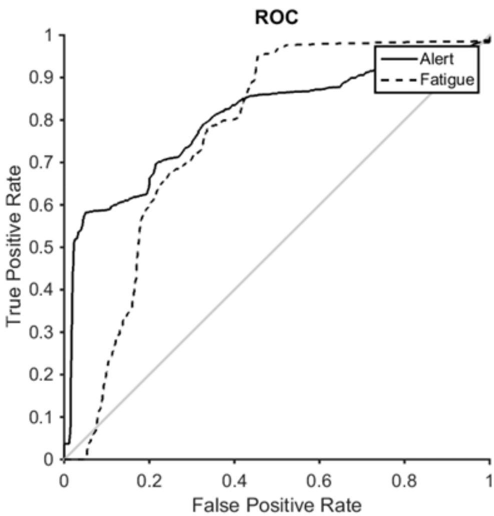
A new multisensor fatigue detection system has been proposed and implemented successfully. The developed prototype was found to be promising in terms of usage low-cost wearable devices to detect fatigue status of operators in real-life environments with an acceptable level of accuracy. The classifiers and the fuser results

Table 2. Summary of system performance.

Output states	ANN classifiers Heart-rate features	 Wrist- temperature features	 Skin- conductance features	Bayesian Fuser
Accuracy	**71.80%**	**70.6%**	**62.20%**	**75.96%**
Sensitivity	**62.00%**	**68.50%**	**79.20%**	**67.76%**
Specificity	**80.60%**	**80.50%**	**59.80%**	**82.71%**



(a) Confusion matrix



(b) Receiver Operating Characteristic

Fig. 10. Example of sub classifiers performance (heart-rate classifier).

demonstrated performance differences relevant to different sizes of dataset or different approaches. The fuser results showed the highest performance of accuracy when comparedto those obtained from the sub-classifiers. Moreover, the fusion algorithm is efficiently applied in modular and distributed system which can base on multi-subsystem with less computing power. The operator individuality is enhanced in labeling process by choosing different levels of threshold based on HRV median divider.

This study is still open for further improvements and verifications that may include but not limited to: (i) conducting a wider study which includes males and females, and different age groups, (ii) extending this study to consider more fusion levels (i.e. data and feature levels), and (iii) Considering more fatigue-related metrics such as behavioral and visual metrics. These improvements and others are currently part of the on-going work of the authors.

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