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Sleep Quality Assessment from Robust Heart and Muscle Fatigue Estimation Using Supervised Machine Learning

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Abstract: Poor sleep quality is a common sign of a variety of sleep and health problems. Thus, sleep quality assessment is necessary as it can be a first-step predictor of physical and mental health. Several studies were completed for this objective. However, no prior study in sleep quality assessment has explored a comprehensive heart rate variability (HRV) analysis by including feature extraction in the time and frequency domain, and non-linear analysis. This study proposed a full evaluation of sleep quality, by incorporating multiple physiological signs in subjects to detect exhaustion after a period of sleep. The primary contribution was the development of an algorithm to estimate sleep quality based on the combination of electrocardiography (ECG) and electromyography (EMG) signals by using machine learning. HRV analysis of ECG signal included time domain, frequency domain, and non-linear analysis. Mean power frequency (MPF) was extracted from the EMG signal by using spectral analysis. In addition, determination of fatigue level as an indicator of the subject's sleep quality was evaluated with fatigue severity scale (FSS) questionnaire. Based on results, the accuracy values of logistic regression, random forest, k-nearest neighbor (k-NN), support vector machine (SVM), and SVM with grid-search were 93%, 93%, 93%, 40%, and 100%, respectively. The proposed method was applicable for investigating sleep quality.

Keywords: ECG, EMG, HRV analysis, Supervised machine learning, Healthy lives.

1. Introduction

Good-quality sleep is a predictor of physical and mental health. Sleep plays an important role in restoring brain performance and will have an impact on body performance [1]. Based on global sleep survey by Philips, 70% of the 13,000 respondents experienced difficulties understanding their sleep [2]. Medically, sleep is the main rest process that the body and mind need [3]. A good understanding of sleep quality is important for health and well-being [4]. Lack of sleep can disrupt immune and endocrine that puts individuals at increased risk of inflammation-mediated diseases such as cardiovascular disease, diabetes, metabolic syndrome, and depression [5].

The sleep quality of a person can be assessed subjectively and objectively. Subjectively, it can be done as an assessment using a questionnaire with a load of sleep-related questions. There are numerous questionnaire-based methods that can be conducted to evaluate sleep quality, such as the pittsburgh sleep quality index (PSQI) [6], the 10-item perceived stress scale (PSS-10) [7, 8], the short form-12 questionnaire (SF-12) [9], or even combination of these methods as conducted by Xu, et al. in [10]. Sleep quality can also be estimated by using information obtained from fatigue severity scale (FSS) questionnaire [11, 12], with the evaluation results were done by Phatrabuddha et al. [13].

Objectively, a person's sleeping condition can be seen from the level of fatigue and sleepiness they have after sleeping. Fatigue and sleepiness are two things that are often used as an indication of not having good quality sleep [14-16]. Fatigue can be detected based on monitoring physiological indicators, which is an objectively effective method to determine the fatigue experienced by a person [17].

Fatigue is a symptom in the body that can be observed or examined by utilizing the body's physiological information. Most physiological processes have accompanying signals that reveal information about their nature or activities. Observation of the physiological condition to assess sleep quality can be done non-invasively by observing signals or information provided by the body [18], such as cardiac electrical and muscle signals [14]. Electroencephalography (EEG) and electrooculography (EOG) can also be used along with cardiac signal generated by electro cardiography (ECG) [19] to measure fatigue and sleepiness.

Muscle fatigue can be assessed using surface electromyography (sEMG) by obtaining mean power frequency (MPF) value, using muscle EMG signals. Since sleep quality depending on whether the body has the correct position during sleep, the body position, especially in the neck, is a crucial concern in sleeping. Poor sleep quality can be due to sleeping position, which will impact fatigue and pain in several parts of the body, such as the neck, shoulders, and lower back [20]. The condition of the muscle state by utilizing muscle signals from the MPF value as a parameter of changes and increasing fatigue conditions has been successfully utilized to analyse a person's fatigue condition [14, 21].

These objective approaches in assessing sleep quality were conducted in prior studies. Sadeghi et al. investigated sleep quality of caregivers of people with dementia (CPWD) based on heart rate variability, electrodermal activity, body movement, and skin temperature [18]. Parameter extraction was calculated to predict sleep quality with a random forest classifier, resulting in an accuracy of 75%. Saini et al. and Babaeian et al. used the k-NN algorithm to detect fatigue in the body by utilizing the body's physiological information [22, 23]. Utilization and retrieval of muscle signal data was used as a parameter of fatigue analysis by Zhang et al. [21]. Nikmatuzaroh et al. estimated driver-impact fatigue with ECG, EMG, and oximeter signals [14]. Similarly, mental fatigue detection was analysed by Huang et al. using wearable ECG [24]. The ECG signal was analysed for heart rate variability (HRV), resulting in three parameters in time domain and five parameters in the frequency domain. The feature extraction result was classified using support vector machine (SVM), k-nearest neighbor (k-NN), naive bayes, and logistic regression. The results showed that the k-NN gave best average result in accuracy, which was 63.5%.

However, the proposed method only used standard feature extraction in the time and frequency domains of ECG signal. Despite the numerous works carried out on the same study, no previous investigation has thoroughly investigated the HRV analysis holistically, namely feature extraction in the time domain, frequency, and non-linear analysis.

Heart rate variability (HRV) is the fluctuation in the time interval between adjacent heartbeats. HRV is generated as a form of interaction between the heart and brain [25], thus it can be used to evaluate the autonomic nervous system (ANS). Evaluation of the ANS can be used as an indicator that provides information on a person's condition, such as sleepiness and fatigue [26, 27]. Fatigue and sleepiness in various situations are conditions that can be obtained information by utilizing HRV with spectral analysis. A study conducted in [27] found that the increased fatigue condition was accompanied by a relatively low value of the low frequency (LF) / high frequency (HF) ratio from HRV, judging by the trend of the data obtained.

To overcome the limitation and weakness of the previous studies, this research aimed to evaluate exhaustion in people after sleeping by combining objective method with a subjective approach. Objectively, this study analysed physiological information parameters from the body, such as body mass index (BMI), cardiac signal, and muscular signal. The main contribution of this study was to develop an algorithm to assess sleep quality by combining ECG and EMG signals using machine learning. In the field of biomedical engineering, machine learning is commonly utilized for classification in applications such as muscular fatigue during exercises [28], multimodal cardiac analysis [29], and classification for liver fibrosis prediction [30].

Based on the ECG signal, this study calculated a more comprehensive HRV analysis by using time domain, frequency domain, and non-linear analysis. The parameters extracted from time domain were root mean sum of squared distance (RMSSD), standard deviation of N-N interval (SDNN), standard deviation of differences adjacent RR intervals (SDSD), and proportion of number in which pairs of RR intervals range by exceeding 50 ms (PNN50). LF/HF ratio was calculated as the parameter from frequency domain. As for non-linear analysis, this study included standard deviation of the short-term RR-interval variability (SD1) and standard deviation of the long-term RR-interval variability (SD2).

Spectral analysis was performed on the EMG signal by calculating the mean power frequency (MPF). Feature extraction from ECG and EMG signals was used to detect sleep quality by

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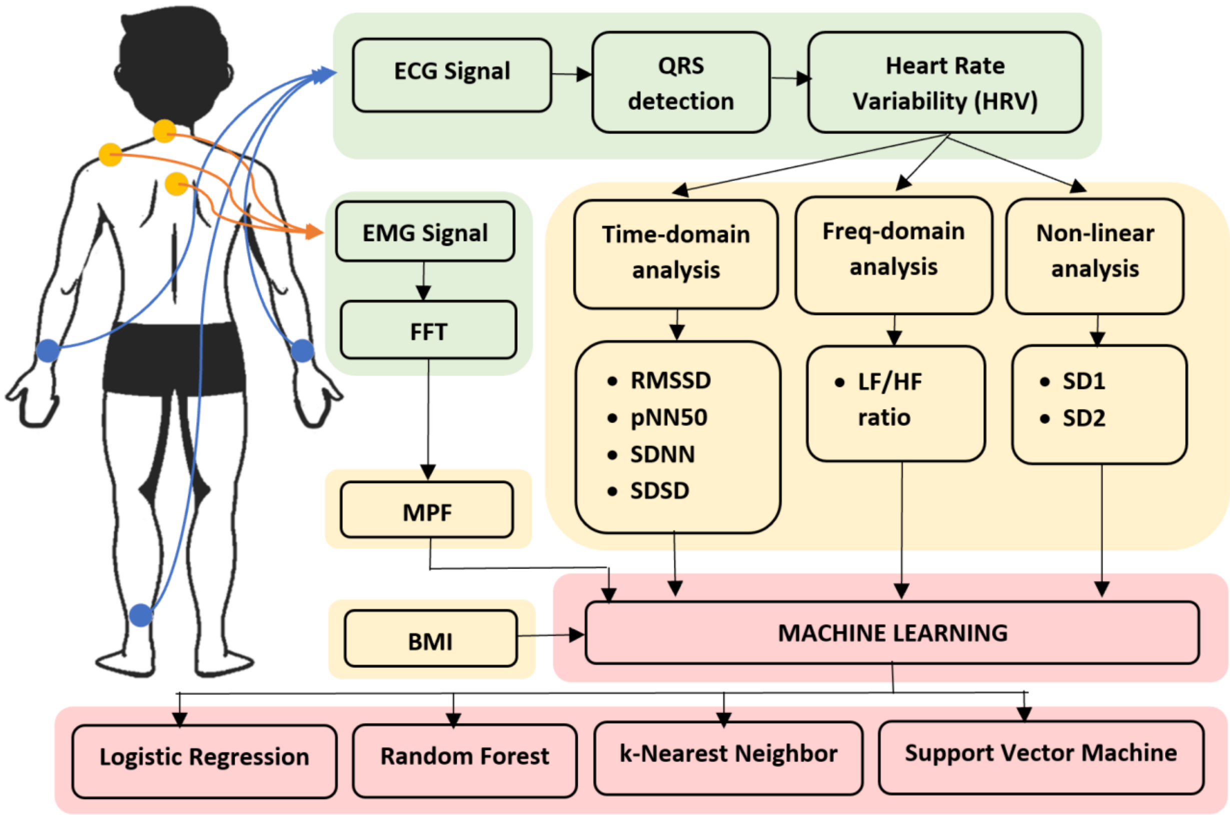

Figure. 1 Block diagram of signal analysis and classification

comparing the confusion matrix on four machine learning algorithms, including logistic regression, random forest, k-NN, and SVM.

Subjectively, determination of fatigue level as an indicator of the subject's sleep quality was evaluated with the results of the FSS questionnaire. The combination of objective and subjective results was expected to give better accuracy in understanding sleep quality, hence improving it.

2. Materials and methods

Objective and subjective assessments are the process used to provide information regarding the estimation of sleep quality. The study involved ten subjects with demographics: male, age range 21 to 22 years old, with a body mass index (BMI) range of 18-30. An objective assessment was carried out by collecting ECG and EMG signals. The ECG signal retrieval process was carried out using surface electrodes placed following the Einthoven triangle rule on the Right Arm (RA), Left Arm (LA), and Left Leg (LL) with Lead III configuration. The ECG signal was recorded with a sampling frequency of 250 Hz as the optimal sampling frequency to record the ECG signal, then analyzed against the HRV of the ECG signal [31]. ECG signal was recorded using the long-term recording for 5 minutes. ECG Click as a module was used to retrieve ECG signals consisting of 7 circuit blocks: protection circuit, pre-amplifier, first high-pass filter (HPF), amplifier, second high-pass filter, low-pass filter (LPF), and driven right leg (DRL) circuit. The EMG signal as the second physiological signal was recorded with a sampling frequency of 2000 Hz as the optimal frequency to analyze the EMG signal [31]. The duration of recording the EMG signal was 10 seconds. EMG signal recording was done using surface electrodes placed on the neck extensor, trapezius transversus, and deltoid, as shown in Fig. 1. EMG Click was used to retrieve EMG signals consisting of a protection circuit, a pre-amplifier circuit, first high-pass filter circuit, amplifier circuit, second high-pass filter circuit, low pass filter circuit, and DRL circuit. ECG and EMG signal retrieval for each subject was recorded five times at different times. A subjective review was carried out at the end of each data collection using the FSS questionnaire. The overall block diagram in this study is shown in Fig. 1. Each part of the block diagram will be explained in the following subsection.

2.1 Research scenario

In this study, data was collected on the subject objectively and subjectively. Participants in the study had the following demographic characteristics. The subject has no history of high blood pressure, diabetes, asthma, or other chronic diseases. To avoid the influence of the subject's physical condition on the quality of their sleep, the participant was selected and evaluated to determine their condition. A total of ten subjects were between the ages of 21 and 22; all subjects were male. Each subject's ECG signal data and EMG signal data were objectively retrieved. The data collection procedure began by ensuring that the subject being tested meets the demographic requirements for the required subject. Ensuring that the subject had slept as a prerequisite for conducting research. Each subject's physiological signals were collected five times, with ECG signals collected for five minutes and EMG signals collected for ten seconds. At the end of each round of retrieving physiological signals, subjective data would be gathered by having the subject fill out a questionnaire using the FSS. The testing and data collection were conducted before the subject engaged in strenuous activity, assuming that the subject would be significantly exhausted after going to bed [32].

2.2 ECG signal processing

The ECG signal processing process was carried out using the QRS detection algorithm with a sampling frequency of 250 Hz. ECG signal data retrieval was recorded for 5 minutes. The QRS complex detection algorithm applied the framework from previous research [33]. The ECG signal was pre-filtered to reduce muscle noise. The result of the pre-filtered ECG signal was realized with a segmentation filter process consisting of LPF and HPF. The following process was parameter extraction, including squaring function, linear envelope, and thresholding processes to detect QRS complexes. QRS complex detection calculated the R-R interval and then plotted the HRV signal.

HRV can provide an overview of the condition of the body because it can explain the activity of the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). HRV was analyzed using the time domain, frequency domain, and non-linear. HRV analysis in time domain includes feature extraction from RMSSD, pNN50, SDNN, and SDSD values. The LF/HF ratio was obtained in performing HRV analysis using the frequency domain. Fast fourier transform (FFT) method was performed on the RR tachogram signal from the R-R interval plot. Power spectral density analysis using FFT method can provide basic information about the frequency distribution to the ultra-low frequency (ULF), very low frequency (VLF), low frequency (LF), and high frequency (HF) regions. Non-linear analysis of HRV was used to determine the physiological condition of the body, one of which was the estimation of sleep quality.

2.3 HRV analysis in time domain

Fatigue affects the sympathetic and parasympathetic nervous systems and can be reviewed using HRV analysis in the time domain. Changes or fluctuations in HRV are a response to physiologic conditions. The RR interval is a time domain parameter that reflects the influence of SNS and PNS. SDNN is the standard deviation of the RR interval in the measurement time range and is specified in (ms). The standard deviation describes how much the distribution of individual RR intervals spreads around the mean value. SDNN can analyze the overall activation of the autonomic nervous system, namely the number of sympathetic and parasympathetic activation. SDNN shows how well the autonomic nervous system can perform regulation in the body. The calculation of SDNN is shown in Eq. (1),

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - \overline{RR})^2} \tag{1}$$

where N is the length of ECG data, RR_i is the i-th RR interval, and $\overline{RR}$ is the average of RR interval.

RMSSD value can indicate how quickly the body can react to stress. In this study, the value of RMSSD can indicate a state of fatigue and non-fatigue. RMSSD is the square root of the mean of the difference between the NN intervals. Processing of RMSSD can be done with Eq. (2),

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N-1}(RR_{n+1} - RR_n)^2} \tag{2}$$

where RR_{n+1} is the following RR interval and RR_n is the current cardiac beat.

pNN50 as one of the HRV analysis parameters in the time domain can be an indicator in the fatigue detection process, considering the trend value of the data obtained. Observing the existing fatigue level was successfully carried out in various conditions such as when doing activities, driving, and not having a good sleep [24]. To calculate this parameter, determine the number of consecutive RR interval pairs with more than 50 ms differences. This value is divided by the number of all consecutive RR interval pairs using Eqs. (3) and (4),

$$pNN50 = \frac{NN50}{N-1}.100\% \tag{3}$$

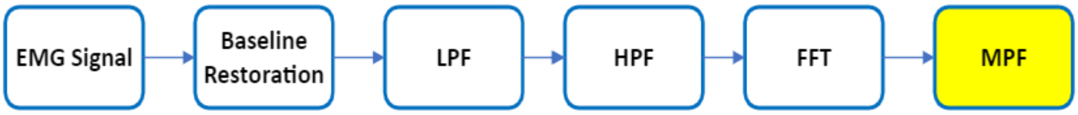

Figure. 2 Diagram of EMG signal processing

$$NN50 = \sum_{i=1}^{N}\{|RR_{i+1} - RR_i| > 50ms\} \quad (4)$$

where *NN50* is the number in which pairs of RR intervals range by exceeding 50 ms.

The related standard deviation of successive RR interval differences (SDSD) only represents short-term variability. SDSD is the standard deviation of differences between adjacent RR intervals that can be calculated using Eqs. (5) and (6),

$$\overline{\Delta RR} = \frac{1}{N-1}\sum_{j=1}^{N-1}\Delta RR_j \quad (5)$$

$$SDSD = \sqrt{\frac{1}{N-2}\sum_{j=1}^{N-1}\left(\Delta RR_j - \overline{\Delta RR}\right)^2} \quad (6)$$

where $\overline{\Delta RR}$ is the average value of differences in RR interval and ΔRR_j is the difference between RR interval in the *j*-th.

2.4 HRV analysis in frequency domain

Fatigue and sleepiness in various situations are conditions that can be obtained information by utilizing HRV with spectral analysis. The power spectral density (PSD) calculation used the fast fourier transform (FFT) method in the frequency domain analysis. After the FFT process is carried out, the results will be obtained in the form of a range of HRV signals into the ULF (0 – 0.003 Hz), VLF (0.003 – 0.04 Hz), LF (0.04 – 0.15 Hz), and HF (0.15 – 0.4 Hz) areas. LF and HF were normalized using Eqs. (7) and (8),

$$LF(n.u.) = \frac{LF}{TP-VLF} \quad (7)$$

$$HF(n.u.) = \frac{HF}{TP-VLF} \quad (8)$$

where *LF(n.u.)* is low frequency in normalized units, *HF(n.u.)* is high frequency in normalized units, *TP* is the total power of frequency in range 0 to 0.4 Hz, *LF* is the power in the low frequency band, *HF* is the power in the high frequency band, and *VLF* is the power in the very low frequency band.

2.5 HRV in non-linear analysis

The non-linear analysis for HRV in this study was based on Poincare plots. Poincare plot analysis can provide detailed information about the behavior of the heart. The graphical representation of Poincare shows that the x-axis is the RR value and the y-axis is RR+1. Parameters calculation from Poincare were SD1 (minor axis of the cloud) and SD2 (major axis of the cloud) values. SD1 is the standard deviation of the short-term RR-interval variability, while SD2 is the standard deviation of the long-term RR-interval variability. Calculations for SD1 and SD2 using Eqs. (9) and (10), respectively,

$$SD1 = \sqrt{\frac{1}{2}SDSD^2} \quad (9)$$

$$SD2 = \sqrt{2SDNN^2 - \frac{1}{2}SDSD^2} \quad (10)$$

where *SDSD* is the variance in the time between successive NN periods as measured by the standard deviation and *SDNN* is the standard deviations of all the NN intervals.

2.6 EMG signal processing

The EMG signal was used as one of the parameters in detecting fatigue. The EMG signal data was retrieved using a surface electrode connected to the EMG Click module. The surface electrodes were connected to the module will be the EMG instrumentation for retrieval of EMG signal data. The stages of the EMG signal process are shown in Fig. 2. EMG signal processing begins with removing the mean of the existing signal. Removing mean was done by subtracting each data in the EMG signal with the average value of the overall data. After removing the mean of the EMG signal, it was continued with filtering by using Butterworth LPF and HPF order 2. The cut-off frequency on the LPF was set to 500 Hz. While the cut-off frequency on the HPF was set to 20 Hz. The cut-off frequency range adapts to the frequency spectrum of the EMG signal. Furthermore, the filtered EMG signal was carried out by the FFT process to determine the value of the mean power frequency (MPF). MPF is calculated using Eq. (11),

$$MPF = \sum_{i=1}^{K} f_i P_i / \sum_{i=1}^{K} P_i \quad (11)$$

where Pi is the power spectrum, fi is the frequency parameter, and K is the length of frequency.

2.7 Machine learning classifiers

Machine learning detected fatigue from the body's physiological information in this study. Parameter values obtained from each subject will be used as a dataset. The dataset consists of 9 features. HRV analysis of the ECG signal produced seven features, the EMG signal performed one feature, and one feature of body mass index (BMI). After getting the dataset, the subjects were asked to complete the FSS survey as a subjective assessment. Based on nine features consisting of RMSSD, SDNN, pNN50, SDSD, LF/HF ratio, SD1, SD2, and BMI values, plus a questionnaire assessment, the dataset will classify sleep fatigue levels using machine learning. Subjects in the study amounted to 10 people. Each subject repeated data collection five times. Therefore, the total dataset was 50. The training and testing data were divided into 70% and 30%, respectively. In this study, the classification method compares four machine learning algorithms, including logistic regression, random forest, k-nearest neighbor, and support vector machine. Performance evaluation of machine learning in this study was carried out by evaluating the confusion matrix. The results of the confusion matrix calculated the value of accuracy, precision, sensitivity, and specificity using Eqs. (12)-(15), respectively,

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{12}$$

$$Precision = \frac{TP}{TP+FP} \tag{13}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{14}$$

$$Specificity = \frac{TN}{TN+FP} \tag{15}$$

where TP (True Positive) is a result where the model correctly predicts the fatigue class, TN (true negative) is a result where the model correctly predicts the non-fatigue class, FP (false positive) is a result where the model incorrectly predicts the fatigue class, and FN (false negative) is a result where the model incorrectly predicts the non-fatigue class.

Logistic regression in regression analysis estimates the parameters of a logistic model. The dependent variable in binary logistic regression is a binary variable with two possible values (0 or 1) that are coded by an indicator variable. The log-likelihood function is maximized by the weights b_0, b_1, ..., b_r that are determined via logistic regression. Once the model has been generated, it must be fitted (or trained). Model fitting involves calculating the coefficients b_0, b_1, ..., b_r that correspond to the optimal cost function value.

Random forests are often applied to issues of regression and classification, where they often yield excellent results even without the need for hyperparameter adjustment. Because of its ease of use, this algorithm is among the most popular in existence. If there is a classification issue, it constructs many decision trees based on various samples and then uses the results of the majority. The N estimator is the desired number of prediction trees to construct before averaging or voting on the results. While increasing the number of trees improves efficiency, it also increases the runtime of the code. Choosing the maximum value of N estimator will result in more accurate and reliable forecasts.

The k-nearest neighbor is a technique for classifying data based on learning data (train data sets) derived from the k closest neighbors (nearest neighbors), where k is the number of neighbors. The newly categorized data is then projected onto a multidimensional space containing k points of learning data. The categorization procedure involves locating the closest k point to the new k point (nearest neighbor). Using the Euclidean distance calculation is the most used method for locating a neighbor. To apply the k closest neighbors technique, the number of k nearest neighbors used to categorize the new data must be determined. Determination of the value of k is considered based on the amount of existing data and the size of the dimensions formed by the data. The number of k should be decreased proportionally to the quantity of data. However, the number of k selected increases as the dimension of the data increases.

Using a supervised learning strategy, support vector machine (SVM) is a machine learning technique that determines the optimal hyperplane or separator function to classify data. When applied to new data, this algorithm clearly categorizes data points by grouping them based on hyperplanes in N-dimensional space (N - number of attributes). The margin is defined as the hyperplane's distance from the support vector. Selecting the hyperplane with the biggest margin from any location in the training data is the purpose of the method. When the dataset is nonlinear or when there are overlapping or mixed classes in the data, SVM kernels are often utilized. In this research, we employed the Gaussian radial basis function (RBF) kernel.

3. Results

The data produced from the objective and subjective evaluation of the research are compiled into a uniform dataset for usage in machine learning methods. Multiple phases of signal processing tests are performed on each existing signal with the objective of getting parameter values that will be used as analysis features. Each signal has distinct stages depending on characteristics associated with the evaluation of sleep quality. In the results and discussion of signal processing, ECG and EMG signals undergo signal processing. The results of each physiological signal processing and sleep quality classification will be discussed in the next subsection.

3.1 Results of ECG signal processing

The initial stage of processing the ECG signal was to obtain a QRS complex detection to calculate the R-R interval. The algorithm for detecting QRS complexes was adapted from the research framework [33]. Fig. 3(a) shows a raw ECG signal containing noise which had been successfully reduced to produce Fig. 3(b). The calculation of the R-R interval plotted in the time domain produced the HRV tachogram shown in Fig. 3(c). After the heart rate value was obtained, the HRV analysis was carried out by applying analysis in the time domain, frequency domain, and non-linear analysis. The time domain was analyzed to obtain features in the form of RMSSD, pNN50, SDNN, and SDSD values. In the frequency domain, it was done to determine the value of the LF/HF ratio of the HRV tachogram and the MPF value of the EMG signal. Non-linear analysis was performed to obtain SD1 and SD2 values. The results of feature extraction in the time domain, frequency domain, and non-linear analysis are shown in Table 1. Based on the results in Table 1, the parameters that most influence the estimation of sleep quality from the level of fatigue are pNN50, LF/HF ratio, and SD1. Meanwhile, other parameters have not shown a significant difference between fatigue and not fatigue. In calculating the LF/HF ratio, the power spectral density of the HRV tachogram was performed based on the frequency distribution of VLF, LF, and HF. The results of the power spectral density are shown in Fig. 4(a). In the non-linear analysis, the Poincare plot shown in Fig. 4(b) was used. Based on Fig. 4(b), the green line as the minor axis is used to calculate SD1, while the blue line as the major axis is used to calculate SD2.

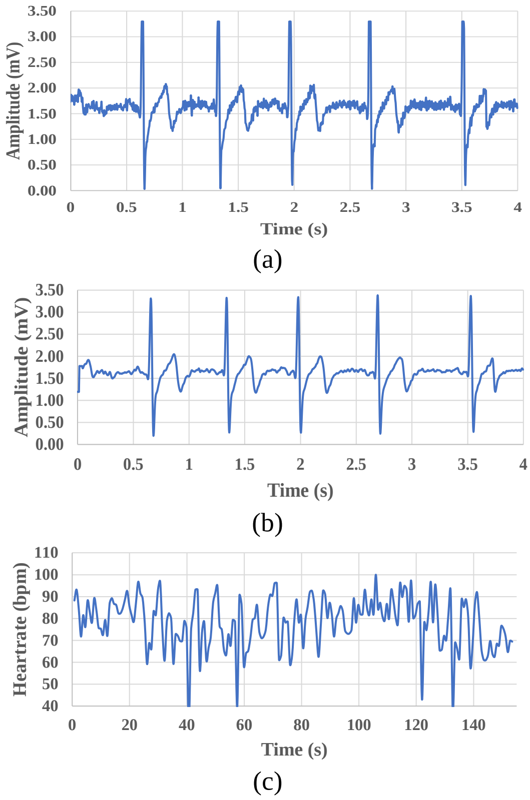

Figure. 3 (a) Raw ECG signal, (b) Filtered ECG signal, and (c) HRV tachogram

3.2 Results of EMG signal processing

EMG as a second physiological signal becomes an objective assessment parameter for fatigue. The EMG signal was taken with a sampling frequency of 2000 Hz. Signal processing applied to EMG signals was baseline removal, low-pass filter, high-pass filter, fast fourier transform (FFT), and continued with feature extraction. The process began with removing the mean of the EMG signal to restore the EMG signal on a baseline basis. Filtering was performed as a follow-up process by applying a low-pass filter and a high-pass filter of order 2 type Butterworth filter with a cut-off frequency of 500 Hz for the low-pass filter and 20 Hz for the high-pass filter. The selection of this cut-off frequency value was based on the spectrum of the EMG signal. After the filtering process, it was continued with the FFT method, which can show the frequency of the EMG signal. The FFT process was applied to the existing signal to get the MPF value of the signal. In the EMG signal processing and feature extraction process, MPF values were obtained for each EMG signal data on the subject. Based on Table 1, the results of the MPF value on non-fatigue subjects are 281.847 ± 8.914 Hz, while for fatigue subjects are 284.226 ± 18.661 Hz. MPF results show that there is no significant difference in estimating sleep quality.

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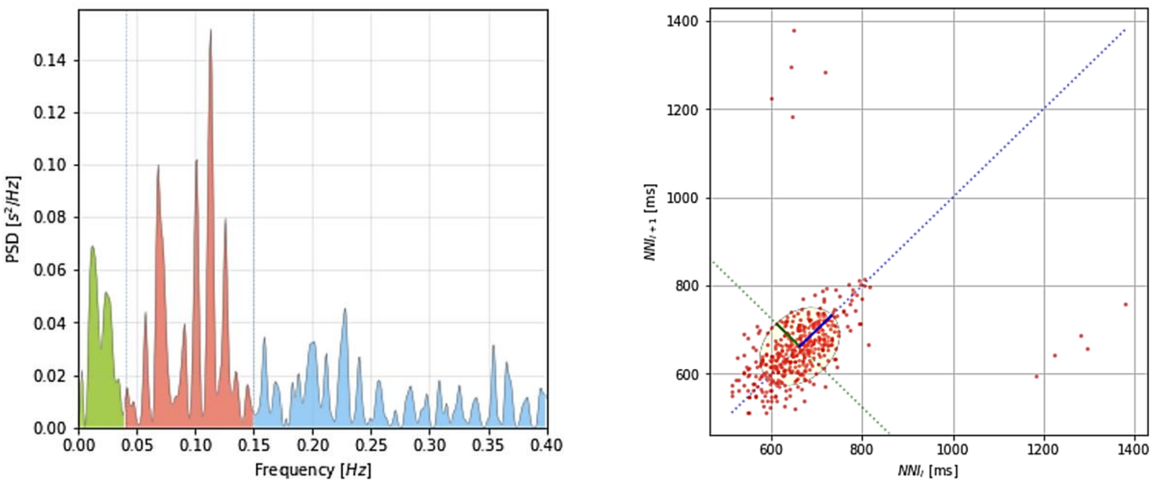
Table 1. HRV analysis and EMG results in time and frequency domains, non-linear extraction

	Parameter (Units)	Class 0 (Non-fatigue)	Class 1 (Fatigue)
Time Domain	RMSSD (ms)	0.033 ± 0.007	0.034 ± 0.007
	pNN50 (%)	0.699 ± 0.645	0.751 ± 0.600
	SDNN (ms)	4.524 ± 0.414	4.512 ± 0.308
	SDSD (ms)	0.001 ± 0.001	0.002 ± 0.003
Frequency Domain	LF/HF ratio (-)	0.647 ± 0.136	0.708 ± 0.235
	MPF of EMG (Hz)	281.847 ± 8.914	284.226 ± 18.661
Non-linear Analysis	SD1 (ms)	79.910 ± 23.952	73.693 ± 17.516
	SD2 (ms)	101.581 ± 26.517	101.027 ± 16.542
	BMI (kg/m^2)	26.358 ± 2.651	22.596 ± 1.751



(a) (b)

Figure. 4: (a) Power Spectral Density of VLF (green), LF (red), and HF (blue) and (b) Poincare plot to calculate SD1 and SD2

3.3 Results of machine learning classifiers

In this study, the dataset was divided into two classes: Low (0) and High (1). This division will be the class for the output of the existing detection system. The classification method if it gives a "LOW" output, shows that the subject has a tendency not to get fatigue to a low level of fatigue. It can be estimated that the subject has good sleep quality, and it can be said that the subject gets enough sleep. When the resulting output is "HIGH", then it shows that the subject has a moderate to severe level of fatigue. This can estimate that the subject has poor or even very poor sleep quality. The process of determining labels or ground truth was based on a review of the subjective assessment of the FSS questionnaire.

The classification process in this study uses logistic regression, random forest, k-NN, and SVM algorithms. The dataset taken from the subject is 50 data, with two classes with a distribution of 24 data for class 0 and 26 data for class 1. The process of scaling the data was done to make it optimal in machine learning. This is because the data range is not the same. The scaling process was only carried out on data features and was not applied for label data. The split process between data features and data labels had been done, followed by training on machine learning. Due to the small number of available datasets, the choice of data split ratio between training and testing has a ratio of 70% and 30%, respectively. Based on Table 2, the best performance classification results are obtained by the SVM algorithm using grid-search optimization. The SVM method uses the radial basis function (RBF) kernel. The parameter values of C and gamma from the RBF kernel are searched through grid-search optimization to determine the highest accuracy. Based on the results of the study, the best C value was 1000 with a gamma of 0.0001. Table 3 shows the confusion matrix findings for the four supervised machine learning techniques. The confusion matrix displays the outcomes of one false positive (FP) and one false negative (FN) data for the logistic regression and random forest methods, while the k-NN provides one false positive (FP) data.

Table 2. Performance classification of test results

	Precision	**Sensitivity**	**Specificity**	**Accuracy**
Logistic Regression	100%	83%	100%	93%
Random Forest	100%	83%	100%	93%
k-NN	83%	100%	90%	93%
SVM	100%	40%	0%	40%
SVM with Gridsearch	100%	100%	100%	100%

Table 3. Confusion matrix results from machine learning classifiers

	TP	**TN**	**FP**	**FN**
Logistic Regression	5	9	0	1
Random Forest	5	9	0	1
k-NN	5	9	1	0
SVM	6	0	0	9
SVM with Gridsearch	6	9	0	0

The SVM approach with grid-search generates the results of the confusion matrix excluding FP and FN based on Table 3.

4. Discussion

The ECG data collected by contacting the body with a sample frequency of 250 Hz was processed to extract the desired ECG signal characteristics. The method of testing signal processing on the ECG signal involved the execution of multiple processing stages to get the necessary characteristics, including time domain and frequency domain parameters, and non-linear analysis of HRV. The ECG signal processing began with QRS detection and could be continued with HRV analysis, where the existing procedures were baseline restoration, lowpass filter, highpass filter, derivative, squaring, moving average, threshold, HRV tachogram, and feature extraction. The objective of baseline restoration was to return the existing signal to its original position. In addition, the raw data was filtered to enhance noise reduction, so that the ECG signal can be retrieved effectively. Beginning the filtering procedure was a lowpass filter of order-2 with a Butterworth filter using a cut-off frequency of 11 Hz. After the lowpass filter process to decrease noise at high frequencies had been completed, the highpass filter process using a second-order Butterworth highpass filter was applied to reduce noise at low frequencies. LPF and HPF had corresponding cut-off frequencies of 11 Hz and 5 Hz. The selection of this cut-off frequency was based on the fact that the spectrum of the ECG signal, particularly the QRS wave, occurred within this frequency range [33, 34].

Following the filtering procedure, the derivative process was applied to the output of the HPF signal in order to sharpen the QRS slop and enhance QRS detection easier. After the process of sharpening the QRS slope on the ECG signal has been completed, proceed with the squaring step to create a signal with a positive amplitude and reduce any remaining noise. The moving average was an advanced process for the squaring process, with the goal of refining the present signal to optimize the next stage of analysis, with a window size of 10. The ECG signal that has been treated to the moving average process will be submitted to a thresholding procedure to generate a signal with high data (1) and low data (0), allowing the R peak in the ECG signal to be easily distinguishable. Based on the RR pulses from ECG data, the heart rate calculation was performed to continue HRV analysis. Fig. 3 illustrates the process of transforming the ECG data into an HRV tachogram.

HRV analysis procedure involved time domain, frequency domain, and non-linear analysis. A time domain analysis was performed to obtain characteristics in the form of RMSSD, pNN50, SDNN, and SDSD values. In the frequency domain, the value of the LF/HF ratio was determined. The power spectral density of the HRV tachogram in the frequency domain is divided into four ranges, which can be seen in Fig. 4(a). Non-linear analysis calculations based on Poincare plots resulted in SD1 and SD2 characteristics. Illustration of SD1 and SD2 based on the results of the Poincare plot can be seen in Fig. 4(b). Parameter values calculated during feature extraction are displayed in Table 1.

As a second physiological signal, EMG involved raw signal processing in order to become an

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Table 4. Accuracy comparison with other studies

	Logistic Regression	Random Forest	k-NN	SVM	SVM with Gridsearch
Huang et al. [24]	59.71%	-	65.3%	57.08%	-
Sadeghi et al [18]	-	75%	-	-	-
Alghwiri et al [35]	71%	74%	-	74%	-
Zhang et al [36]	-	-	-	65.74%	-
Wang et al [37]	-	-	61.92%	80.67%	-
Proposed Method	93%	93%	93%	40%	100%

objective review parameter. Using a sampling frequency of 2000 Hz, the EMG signal was recorded. The EMG signal was subjected to baseline elimination, lowpass filter, highpass filter, fast fourier transform (FFT), and then feature extraction. The procedure began by eliminating the mean of the EMG signal, with the goal of resetting the EMG signal to its baseline value of 0. A lowpass filter and a highpass filter of order-2 Butterworth filter with a cutoff frequency of 500 Hz for the lowpass filter and 20 Hz for the highpass filter were used to filter the signal. The selection of this cutoff frequency was based on the reason that the EMG signal spectrum falls within this frequency range [28]. After the filtering step was completed, the fast fourier transform (FFT) procedure performed. The FFT algorithm was utilized to determine the MPF value of the EMG signal. As displayed in Table 1, MPF values are obtained during the EMG signal processing and feature extraction phase.

Nine feature extractions were tested using four machine learning methods. A total of 50 data with nine features are divided into 70% training data and 30% testing data, amounting to 35 and 15 data, respectively. In Logistic Regression, the intercept b_0 was 22.94 and the weight coefficients b_1 to b_9 which can maximize the log-likelihood function of -2.12, 0.01, 0.02, 0.02, 0.01, 0.04, -0.24, 0.03, and 0.15. In random forest, the *N* estimator is the number of trees to build before maximum voting or average predictions. A higher number of trees improves performance. In this study, the N estimator of 50 was used due to quite a lot of features. K-nearest neighbors is an algorithm for classifying data based on learning data derived from the *k* closest neighbors (nearest neighbors). In which *k* is the total number of nearest neighbors. In this study, the optimal *k* used for binary classification of sleep quality was 30 using Manhattan distance metrics. support vector machine (SVM) method is usually used to perform linear regression and problems for classification purposes. The SVM kernel has the same logic as SVM. The difference is that in the SVM kernel, the algorithm performs data mapping based on certain kernel functions. The SVM kernel has more flexibility for non-linear data because it can add more features to use to maximize the hyperplane. Radial Basis Function was used as the SVM kernel in this research. Furthermore, the results of the grid-search obtained the optimal gamma value of 0.0001. Based on the test results in Tables 2 and 3, the best machine learning method used for classifying sleep quality is SVM.

In the proposed method, two multimodal signals, ECG and EMG, with nine properties were evaluated. In terms of sleep quality, there was no statistically significant variance in the RMSSD, SDNN, and SDSD parameters in the temporal domain for fatigued and non-fatigued participants. In the frequency domain, the LF/HF ratio parameter varied between the two classes, with a mean of 0.647 for the non-fatigue class and 0.708 for the fatigue class. In nonlinear analysis, the average SD2 value for both classes was around 101 ms. The SD1 parameter had a considerable difference between the non-fatigue and fatigue classes, with values of 79.910 ms and 73.693 ms, respectively. This study indicated that the proposed method is adequate for classifying sleep quality fatigue levels using only four characteristics, namely pNN50, LF/HF ratio, SD1, and MPF of EMG signal. Furthermore, fatigue recognized after sleep using ECG and EMG signals requires only four features for binary classification.

The results of this study were also compared with other works, as shown in Table 4. Huang et al. conducted research into the possibility of mental tiredness using wearable smart electrocardiogram (ECG) equipment [24]. In their proposed method, a number of HRV measures, including the NN mean, pNN50, TP, and LF, were used for detecting mental fatigue. The k-NN exhibited the highest average CV accuracy of the four methods, 65.3% across all feature combinations. Study conducted by Sadeghi et al. [18], gave 75% accuracy with random forest classifier. Four physiological features were considered in this study, which were HRV, electrodermal activity, body movement, and skin temperature. Another objective approach can be done by utilizing brain signal generated by EEG, as conducted by Zhang et al. [36] and Wang et al. [37]. Wang et al. method in using 9 features generated by minimal-redundancy-maximal-relevance (MRMR) and brain topography, resulted in better accuracy as high as 80.67%. Subjective approach in assessing sleep quality also apparent, represented by Alghwiri et al [35], in which method utilized PSQI index. The best accuracy achieved in this study was 74% by using random forest and SVM classifier.

However, among the all-found prior studies, none has combined objective method with subjective approach. Our proposed method utilized physiological parameters from ECG and EMG, combined with subjective approach from utilizing FSS questionnaire. Additionally, a more comprehensive HRV analysis also considered by including the non-linear analysis. The proposed method achieved accuracy as high as 100% by using SVM classifier with grid-search. This comparison shows that the proposed method achieved better accuracy result compared to other studies.

This research has made a substantial contribution to knowledge, but it also has notable limitations. Clearly, the ECG and EMG signals are impacted by a variety of physical characteristics, including perspiration and motion artifacts. For future research, it is suggested that EEG signal be used as a criterion for determining data labels.

5. Conclusions

This study proposed multiple methods for detecting fatigue in people following a duration of sleep, including the use of physical condition assessments as the criteria for formulating sleep quality. The use of physiological information in the form of ECG and EMG signals is very useful in estimating the state of fatigue after sleeping. The existing signal data was taken and recorded with the ECG module and EMG Click was performed on ten healthy subjects. ECG signal retrieval applies long-term recording to produce RMSSD, pNN50, SDNN, and SDSD features. In the EMG signal, MPF parameter retrieval process was carried out. The features obtained from the two signals were analyzed to detect the sleep quality of the subjects. Based on the results of the study, the parameters that most differentiated the subject's level of non-fatigue and fatigue were pNN50 (0.699 ± 0.645 % and 0.751 ± 0.600 %), LF/HF ratio (0.647 ± 0.136 and 0.708 ± 0.235), SD1 (79.910 ± 23.952 ms and 73.693 ± 17.516 ms), and MPF of EMG signal (281.847 ± 8.914 Hz and 284.226 ± 18.661 Hz). Furthermore, nine features were applied to the four machine learning algorithms. The accuracy scores for SVM without kernel, random forest, logistics regression, k-NN, and SVM with grid-search are 40%, 93%, 93%, 93%, and 100%, respectively, in the results of assessing the classification performance of supervised machine learning. The results of the best confusion matrix for sleep quality detection using SVM of RBF kernel with gridsearch optimization. Further research can be carried out by labeling subject data not only by subjective assessment in FSS survey, but by objective assessment, such as using EEG signals

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, writing original draft preparation, writing review and editing, visualization: Nada Fitrieyatul Hikmah. The supervision and project administration: Rachmad Setiawan. The data collection and research scenario: Mohammad Daffa Gunawan.

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