Development of A Driver Drowsiness Monitoring System Using Electrocardiogram

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***Abstract*—Driver drowsiness has become a common issue that leads to road accidents and death. Accidents not only affect the physical body of the driver, but it also affects people in the surrounding, physical road conditions, and environments. It is proven in previous studies that biological signal are closely related to a person's reaction. Electrocardiogram (ECG), which is an electrical indicator of the heart, provides such criteria as it reflects the heart activity. Morphological signal of the heart is strongly correlated to our actions which relates to our emotions and reactions. Thus, this study proposed a non-intrusive detector to detect driver drowsiness by using the ECG. A total of 10 subjects were obtained from The Cyclic Alternating Pattern (CAP) Sleep database. The signals are later processed using low pass Butterworth filter with 0.1 cutoff frequency. Then, QRS complexes are extracted from the acquired ECG signal. Classification techniques such as RR interval and different of amplitude at R peak were used in order to differentiate between normal and drowsy ECG signal. Cardioid based graph was used to support the argument made in analyzing area and circumference of both normal and drowsy graph. The result shows that RR Interval of a drowsy state increased almost 22% rather than in normal state. The percentage different of amplitude difference at R peak between normal and drowsy state can reach up to 36.33%. In terms of cardioid, area, perimeter and Euclidean distance of the centroid are always higher than drowsy. Thus, from the outcomes that been suggested for drowsiness detection using RR interval and amplitude of R are able to become as the most efficient drowsiness detection.**

***Index Terms*—Cardioid; Drowsiness; Electrocardiogram; R peak; RR Interval.**

I. INTRODUCTION

Accidents and death on the road has become a national issue in Malaysia. For the past decade, car accidents are one of the main contributors to road accidents and might lead to road deaths. Most of road accident statistics increased during school holidays and festive seasons [1]. It does not only bring harm to the victim's family but it also affects the country in loss of human capital. According to the Head of Traffic Department in the Royal Malaysia Police (RMP), Dato' Mohd Fuad Abd Latif, the common causes that lead to road accidents is the attitude of the driver itself [2].

In order to minimize the road accidents and reduce the habits falling asleep while driving, there have been a few techniques from the past that used various approaches to identify the drowsy state of a driver which is in terms of physiological measures. For example, electrocardiogram (ECG) can been applied in measuring the Heart Rate Variability (HRV) using the RR Interval. Based on the recorded ECG data, information such as recognizing the healthcare information and the abnormality of a subject such as drowsiness and fatigue state can be illustrated [3].

In order to improve the convenient on a driver's body while taking accurate signals, many researches implement wearable devices to detect the drowsy state of a driver. This study proposed a non-intrusive technique to detect driver drowsiness by using the ECG. A total of 10 subjects were obtained from The Cyclic Alternating Pattern (CAP) Sleep database to simulate the scenario of normal and drowsy conditions. Then, measured ECG signals were analyzed to determine whether the subject is in normal or drowsy state.

II. LITERATURE REVIEW

Most of the previous works propose techniques which include the convenience and driver's safety way to detect the drowsiness. This section briefly discusses related literatures on driver drowsiness monitoring system.

Shin et al. in [4] proposed the design of ECG sensor to obtain physiological signals that consists of conductive fabric electrodes and PPG sensor for monitoring car driver's condition. Two subjects have been tested through normal and drowsy states in the day and night for a duration of three minutes. In order to recognize drowsiness and fatigue cause, this study analyzes the frequency domain using the power spectrum of HRV signals. The outcomes of the frequency domain analysis were shortened and negative emotions such as drowsiness were distinguished by using power spectrum density (PSD). A ratio of 6 which has been derived from the HRV analysis classifies the car driver in a drowsy condition. Thus, the study shows that the driver's drowsiness state is proved by the variation of different low frequency (LF) and high frequency (HF) ratio during different condition. However, not all the time the driver will put his hand on the specific position of the sensor on the steering wheel which causes the failure of the sensor to acquire signal.

Warwick et al. in [5] designed an accessible driver detection system with wireless wearables using BioHarness 3 to detect driver drowsiness. The experiment was conducted within 15 subjects. BioHarness 3 was attached to the subject's chest, and then the subjects will feel drowsy and simultaneously make them go to sleep. The outcome shows that breathing rate (BR) will drop quickly in 39 seconds when a subject falls asleep while most of the decrease for all experiments was approximately 4 breaths per minute. In terms of heart rate (HR), it begins to increase just before falling asleep. For all the experiments completed, the increase began nearly 27 seconds earlier to fall asleep and a maximum of almost 15 seconds after falling asleep. There was a rise of 15 beats per minute in 42 seconds when the variation occurred which showed noticeable differences in terms of the BR. However, BioHarness 3 is not a good indicator in measuring HRV since the results are not consistent. Thus, future investigation should be performed to overcome this issue.

Omidyeganeh et al. in [6] applied the result of yawning and merging the eye closure to develop a combine method to increase drowsiness detection efficiency. The idea of the study begins with ten video sequences taken from different angle and light intensity within different subject. First, image that been captured is used to extract the face region. Second, detect the eye area in the face. Third, mouth should be recognized in the face area. Then, extracted mouth and eye features are used to detect the yawn and eye closure. Next, a decision is made on the drowsiness of the driver if the results are fused. Finally, if a drowsy state is achieved at a certain threshold, an alert is sent to the driver. Structural Similarity Measurement (SSIM) was applied and the result shows the accuracy of the face detection is 98% for the database. However, the study didn't mention whether the driver wear hats or glasses which would affect the performance of the technique applied.

Ingre et al in [7] proposed an experiment based on Standard Deviation of Lane Position (SDLP) using numerical statistics derivative that can be used in measuring the level of driver drowsiness. SDLP is given by the software itself while in the case of conducting the experiment, external camera has been used in order to track the position of the lane. From this study, it found that increasing the SDLP (meters) will increase the Karolinska Sleepiness Scale (KSS) ratings. SDLP measurements of 0.19, 0.26, 0.36 and 0.47 are formed by the corresponded of 1, 5, 8, and 9 of the KSS ratings, respectively. However, SDLP can also be affected by any sort of impaired driving, including driving under the impact of alcohol or other drugs, especially for the drug sedatives.

Otmani et al. in [8] proposed a driver drowsiness detection approach using Steering Wheel Movement (SWM). It is measured using steering angle sensor mounted on the steering column; the driver's steering behavior was measured. The study found that sleepy drivers can be detected on fewer steering wheel reversals than normal drivers and the researcher decided that only small number of steering wheel movements (between 0.5° and 5°) was considered which required adjustment of the lateral position within the lane position. However, this method did not consider the angle of the car moving in a straight line although the driver is drowsy.

As a summary, there are many ways to discover driver drowsiness such as motor vehicle, behavioral and physiological based methods. However, there are still lacking to be a better system for a driver monitoring system. According to Healey et al. in [9], physiological measure is the best measurement in measuring signal in a body. One of the advantages of ECG is that it can detect internal signal more accurate than using other measures. Thus, due to this advantage of ECG, this study proposed a development of a driver drowsiness in monitoring system using ECG.

III. METHODOLOGY

In this section, the proposed system are consists of data acquisition, pre-processing, feature extraction and classification that will be explain briefly in the next subsection.

A. Data Acquisition

ECG data used in this study were collected from the Cyclic Pattern (CAP) Sleep database that can be accessed from Physionet[10]. The database consists of 10 polysomnographic subjects that are registered at Sleep Disorders Center of the Ospedale Maggiore of Parma, Italy. The duration of each ECG signals recording is 10 seconds.

B. Pre-processing

Raw signal collected might not be in a smooth waveform due to the occurrence of the noise which is caused by the surrounding environment while collecting the data. In order to remove the unwanted signal, data processing is performed by using lowpass filter into the raw signal since low pass filter permits the use of low amplitude thresholds to have high sensitivity detection. So, Butterworth filter is used as a digital filter.

C. Feature Extraction

In this method, R wave is chosen as the reference point because it is the most prevalent point in the QRS complex as shown in Figure 1, and then equal points from the left and right of the reference R will be selected until this study obtained the QRS complex. QRS is selected for data extraction is because QRS is less affected by the noise.

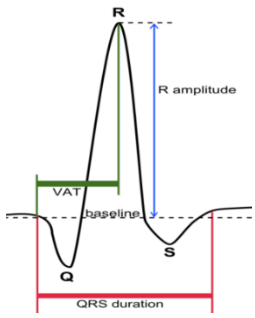


Figure 1: QRS Complex [11]

D. Classification

There are 3 classifiers that been chosen in extracting the data which are i) RR interval, ii) Difference of amplitude at R peak and iii) Cardioid based graph by analyzing on the area, Euclidean distance and perimeter of both normal and drowsy graph. Each of these decision making techniques will be briefly described next.

a. RR Interval

Previous studies prove that RR interval can be used as an indicator for HRV analysis [12]. RR interval is the period between the first R peak and the next R peak. RR interval can be used to measure drowsiness since the R peak is less affected by noise that leads to small error and accurate measurements than the other points.

b. Difference of Amplitude at R Peak

The measurement of R amplitude can also be used to analyze the ECG signal. ECG signal clearly shows that amplitude of R is the highest peak in QRS complex. Different peak of R can be considered as an indicator to differentiate between normal and drowsy state.

c. Cardioid Based Graph

It is proven in previous studies that Cardioid based graph as shown in Figure 2 can increase the accuracy of the results to support other classification algorithms [13].

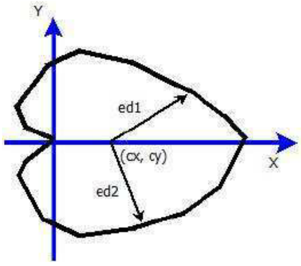


Figure 2: Cardioid Based Graph

Centroid, area and perimeter can be determine using MATLAB command called polygeom function by using Equation (1).

$$polygeom(xx(1{:}end\text{-}1),yy) \quad (1)$$

where xx is the data of the signal and yy is the second derivation of xx in the Cardioid graph. The centrois is used to analyzed the Euclidean distances, ed(i) using Equation (2). Euclidean distance is the radius of the Cardioid graph.

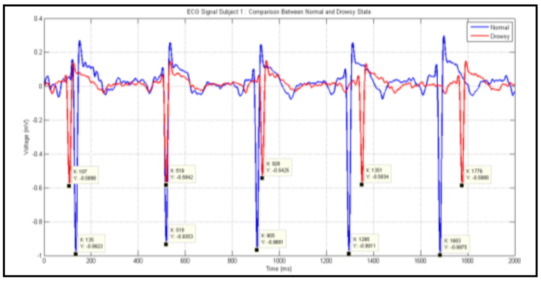
$$ed(i) = \left[\sqrt{(c(y) - y(i))^2 + (c(x) - x(i))^2}\right] \quad (2)$$

In order to show our experimentation of the study, results of five subjects will be describe from a total of ten subjects used in this work from the CAP Sleep database.

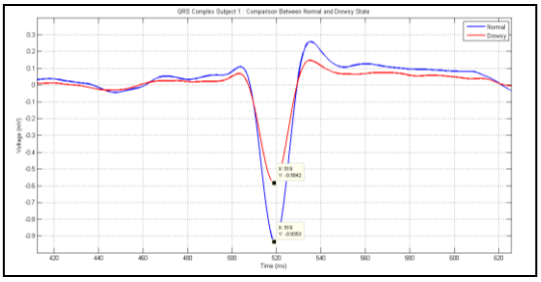
IV. Experimentation and Results

In this chapter, the Cyclic Alternating Pattern (CAP) Sleep Database was used since this database includes the signal of subjects in the state of drowsiness. QRS complex was applied in this database to check whether this proposed technique manage to differentiate between drowsy and normal condition. Then, classification algorithm such as using difference of amplitude at R peak and RR interval was used in order to classify the signal between normal and drowsiness condition of a subject. In order to prove the result, Cardioid based graph also been applied in increasing the result accuracy.

In order to show our experimentation of the study, results of three subject will be describe from a total of ten subjects used in this work from the CAP Sleep database. These data can be accessed freely that are available online from PhysioNet. Then, the signal was processed using low pass filter with second order and normalized cut off frequency of 0.1 Hz in MATLAB and the resultant signal can be seen in figure (a) of each subjects. After the signal had been filtered, QRS complex is used to extract the data in figure (b) of each subject. At this point, RR interval and difference of amplitude at R peak are calculated. Cardioid based graph is applied to prove the result in figure (c) of each subject by calculating the area, Euclidean distance and perimeter. All these figures (a, b, and c) are shown in Figure 3, Figure 4 and Figure 5, respectively.



(a)



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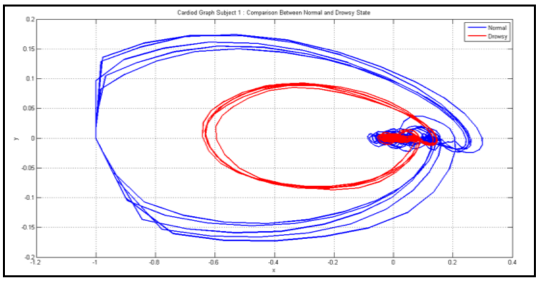
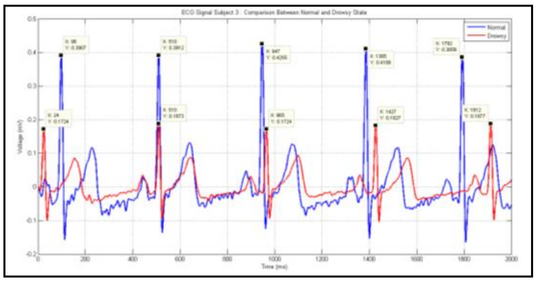


(c)

Figure 3: (a) ECG Signal Subject 1: Comparison between Normal and Drowsy State; (b) QRS Complex Subject 1: Comparison between Normal and Drowsy State; (c)Cardioid Graph Subject 1: Comparison between Normal and Drowsy State.



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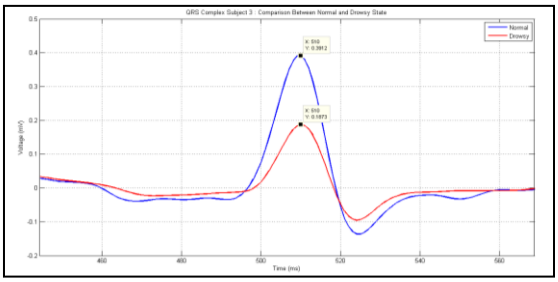

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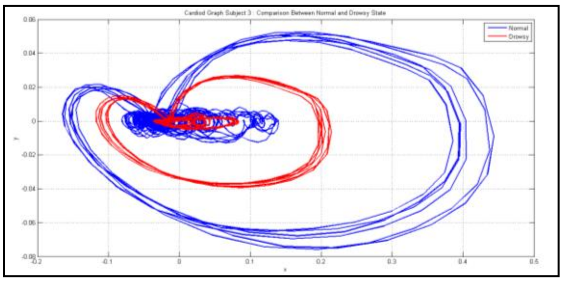
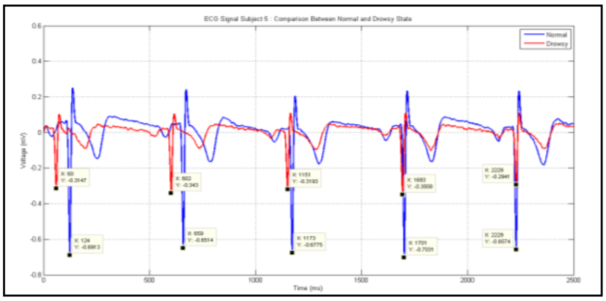


Figure 4: (a) ECG Signal Subject 3: Comparison between Normal and Drowsy; (b) QRS Complex Subject 3: Comparison between Normal and Drowsy State; (c) Cardioid Graph Subject 3: Comparison between Normal and Drowsy State.



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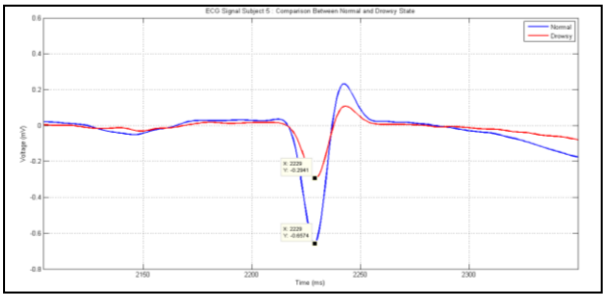
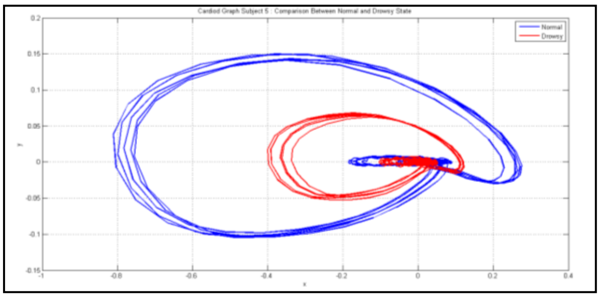


(b)



(c)

Figure 5: (a) ECG Signal Subject 5: Comparison between Normal and Drowsy State; (b) QRS Complex Subject 5: Comparison between Normal and Drowsy State; (c) Cardioid Graph Subject 5: Comparison between Normal and Drowsy State.

Table 1
RR Interval of Ten Subjects

Subject	RR-Interval Normal (ms)	Drowsy (ms)	Percentage Difference (%)
1	387.00	417.25	7.82
2	333.20	406.50	21.99
3	423.50	472.00	11.45
4	345.25	376.50	9.05
5	526.25	542.25	3.04
6	519.50	547.00	5.31
7	389.75	406.50	4.30
8	401.67	411.00	2.32
9	308.00	360.00	16.88
10	439.33	463.67	5.54

The previous figures have been analyzed to identify the trend in both conditions: normal and drowsy states. RR Interval is used as one of the classifier to recognize the differences between both normal and drowsy state by measuring the distance of selected R Peak to another cycle of R Peak in Table 1. The result shows that RR Interval of a drowsy state increased almost 22% rather than in normal state. These results behave as it because the driver is in a normal state where the heart rate will be constantly active. Ironically, if the driver is in drowsy state this would to slower heart rate. Thus, this suggests that the result when of drowsy state has a longer duration of RR Interval rather than in normal state.

Table 2
Difference of Amplitude at R peak of Ten Subjects

S	Amplitude Difference at R-Peak (mV) A	B	C	D	E	F	G
1	0.9923	0.9353	0.5898	0.5842	0.3511	0.0570	0.0056
2	0.6873	0.6000	0.5035	0.5158	0.0842	0.0873	0.0123
3	0.3907	0.3912	0.1724	0.1873	0.2039	0.0005	0.0149
4	0.3373	0.3691	0.2509	0.2322	0.1369	0.0318	0.0187
5	0.7031	0.6574	0.3508	0.2941	0.3633	0.0457	0.0567
6	0.5858	0.6279	0.4591	0.4533	0.1746	0.0421	0.0058
7	0.2783	0.2724	0.1527	0.1420	0.1304	0.0059	0.0107
8	0.5806	0.5681	0.4933	0.4228	0.1453	0.0125	0.0705
9	0.4298	0.4498	0.1880	0.1817	0.2681	0.0200	0.0063
10	0.6497	0.7742	0.5724	0.5999	0.1743	0.1245	0.0275

Hint: S= Subject; A= Normal, $|n_1|$; B= Drowsy, $|d_1|$; C= Normal, $|n_2|$; D= Drowsy, $|d_2|$; E= Amplitude Difference, $|n_2\text{-}d_2|$; F= Amplitude Difference, $|n_2\text{-}n_1|$; G= Amplitude Difference, $|d_2\text{-}d_1|$

Next, difference of amplitude at R peak from QRS complex is used as a classifier by synching the same duration of any R peak for normal and drowsy state. Then, both amplitudes were calculated in three conditions, that is in normal-to-drowsy, normal (current)-to-normal (previous) and drowsy (current)-to-drowsy (previous) amplitude difference as shown in Table 2. It clearly shows that normal amplitude at R peak is always higher than drowsy amplitude at R peak. This output shows that when a driver is in normal condition, a lot of movements will be made as compared to when the driver is in a drowsy state. This situation will affect the amplitude of R where the R peak will become lower in drowsy state as compared to normal state due to less movement of the body.

Table 3
Cardioid Based Graph: Area and Euclidean Distance of Ten Subjects

Subject	Area Normal	Area Drowsy	Euclidean Distance Normal	Euclidean Distance Drowsy
1	1.5549	0.4997	0.2984	0.1471
2	0.6104	0.2304	0.2369	0.0741
3	0.3158	0.0883	0.4806	0.0591
4	0.2613	0.1089	0.1117	0.0727
5	0.9273	0.2030	0.2750	0.1501
6	0.5765	0.3390	0.2028	0.1774
7	0.5969	0.2359	0.3600	0.0538
8	0.2524	0.1919	0.6196	0.5707
9	0.4380	0.1338	0.4865	0.1072
10	0.7255	0.4178	0.1276	0.0844

Cardioid Based Graph is applied to prove the previous result by considering the aspect of area, Euclidean distance and perimeter of a cardioid between both states. Based on Table 3, normal state of ECG signal requires larger area and higher Euclidean distance rather than being in drowsy state. The results illustrate that when a larger Cardioid graph is obtain, the subject are in an active situation while in drowsy state, the subjects will be in rest state that represent to a smaller Cardioid graph. Theoretically, the increasing of Euclidean distance of Cardioid will increase the perimeter of the graph in normal state.

Table 4
Cardioid Based Graph: Centroid and Perimeter of Ten Subjects

Subject	Centroid		Perimeter	
	Normal	Drowsy	Normal	Drowsy
1	(-0.4190,0.0035)	(-0.2579,0.0027)	21.0752	13.0965
2	(-0.2413,-0.0029)	(-0.2027,-0.0049)	19.1750	9.4176
3	(0.1415,-0.0103)	(0.0587,-0.0071)	14.4921	6.3567
4	(-0.1520,0.0032)	(-0.1115,0.0030)	10.8974	5.7375
5	(-0.3123,0.0230)	(-0.1493,0.0092)	15.7096	9.2344
6	(-0.2924,0.0213)	(-0.2211,0.0169)	14.9198	11.5885
7	(-0.0755,-0.0301)	(-0.0665,-0.0191)	15.2417	9.0502
8	(0.2720,0.0022)	(0.2417,0.0014)	8.6200	7.2355
9	(0.0369,0.0251)	(-0.0595,0.0139)	15.0764	6.8250
10	(-0.3761,0.0051)	(-0.2920,0.0051)	13.9512	10.2953

Next, perimeter of Cardioid also can be used as an indicator in drowsiness detection. Perimeter of Cardioid is analyzed by measuring the circumference of the cardioid. Theoretically, the increasing of Euclidean distance of cardioid will increase the perimeter of the graph in normal state. The comparison of normal and drowsy state in aspect of perimeter is shown in Table 4. These results have the ability to represent the study of drowsiness using ECG signals.

V. Conclusion and Future Work

As a conclusion, the objectives of this study have been successfully achieved. This study was established as an efficient method on driver drowsiness monitoring system using ECG and been conducted with the deep understanding of all the stages in this study which are data acquisition, pre-processing, feature extraction and classification such as RR interval, difference of amplitude at R peak and Cardioid graph. Based on the result, RR interval of drowsy state shows that it takes almost 22% of the RR interval change rather than in normal state. In terms of amplitude difference of R peak, it shows that amplitude of normal state at R peak is much higher as compared to drowsy state. The percentage different between normal and drowsy state can reached up to 36.33%. In order to check the consistency of normal data and drowsy data, the result prove that minimum normal data difference with other normal data is 0.05% and minimum drowsy data with other drowsy data is 0.56%. The experimentation results suggest that the data is constantly stable throughout this study. As to verify the previous outcomes, Cardioid based graph was applied to support these results. The output states that normal ECG data is constantly having larger values of area, Euclidean distance and perimeter than drowsy ECG data.

Even though vital step is crucial as it determines whether a driver is drowsy or in a normal condition, there will be some room for improvement for this study as stated below:

Real Time ECG Data: This study is using a database from Physionet that are freely accessed. In order to verify the accuracy of the suggested technique, it is preferred to acquire real time data. This is due to some parameters that can't be change if we used online database. By having our own data, we might be able to increase our accuracy of this proposed technique.

Data Acquisition Device: Since this study has limitation in taking the real time signal due to the device limitation can't record ECG signal more than 30 seconds, so by having a device that can record ECG signal with a longer period might help on the improvement of the effectiveness of the proposed system.

Acknowledgment

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