Real Time Driver Drowsiness Detection Using a Logistic-Regression-Based Machine Learning Algorithm

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Abstract- The number of car accidents due to driver drowsiness is very steep. An automated non-contact system that can detect driver's drowsiness early could be lifesaving. Motivated by this dire need, we propose a novel method that can detect driver's drowsiness at an early stage by computing heart rate variation using advanced logistic regression based machine learning algorithm. Our developed technique has been tested with human subjects and it can detect drowsiness in a minimum amount of time, with an accuracy above 90%.

Index Terms—Driver drowsiness detection, electrocardiogram, heart rate variation, machine learning

I. INTRODUCTION

The increasing number of car accidents due to driver drowsiness has been a challenge for many authorities and automobile companies. The National Highway Traffic Safety Administration's (NHTSA) report [1] indicates that in 2009 over 70,000 car accidents were caused by driver drowsiness, out of which 700 of them resulted in fatalities and 36,000 of them resulted in injuries, excluding crashes not reported. Drowsiness can be caused by sleep loss, low circadian rhythm, and driving for an extended period of time [19]. In order to detect drowsiness in early stages, there have been many methods developed with the help of sensors mostly associated with many different physiological signals such as electrocardiogram (ECG) and others. Current research included studies that record and analyze a driver's blinking pattern and studies that monitor brain electrical behavior to detect driver drowsiness. In our research, the focus is on ECG signal variation in transition to drowsiness and detection of the changing ECG signal behavior to accomplish high accuracy in less time.

In order to implement a drowsiness detection system, a hardware and software system capable of detecting electrical signals generated by the heart in real time and predicting the states of drowsiness needs to be designed. A hardware system was designed to detect an ECG signal, amplify the ECG signal and to remove unwanted noise. The challenge was to detect the drowsiness in the lowest possible amount of time for the safety of the driver [17]. Our goal is to detect drowsiness in a few seconds, after the driver starts driving, while maintaining a level of accuracy above 90% [18]. It was suggested that measuring the ratio of low frequency to high frequency of the heart rate variation (R complex peak to the next R complex peak) as an indicator for drowsiness would be effective. However, due to the fact that average heart beat is approximately 90 beats per minute, there is minimum of 5 minutes of ECG data that is required to extract at least three hundred peak to peak detection to evaluate driver drowsiness [10]. This is too long of a period where there is no detection of drowsiness, during which a driver could find himself or herself in a hazardous scenario before the required data has been gathered.

In [18] authors suggest implementing a system based on non-contact ECG sensors to detect the electrical signal from the heart. Authors suggest different material such as Silver (Ag) or AgCl for the surface of non-contact sensors in order to maximize the signal-to-noise ratio. Since a driver does not always wear the same clothing material, the impedance matching between the body sensors and the clothing varies. This variation in material of clothes leads to more noise and a lower ECG amplitude. The challenge to increase signal to noise ratio was addressed in [7] and authors proposed implementing a differential amplifier and reducing noise with a feedback technique called driven-right-leg (DRL). Adding a set of adaptive filters to remove the baseline noise in order to receive a clean ECG signal is suggested in [19]. Effective noise removal techniques deliver a clean ECG signal to the processor and increase accuracy, therefore minimizing detection time.

In this paper, a novel driver drowsiness detection technique is proposed which employs logistic regression method based on the machine learning approach. Our proposed approach contains the following attributes

- Lowering detection time: By developing a unique algorithm for each person, a small window of an ECG signal suffices for early detection.
- Increasing accuracy: The algorithm detects outlier data and removes them before detection, thereby increasing accuracy.
- Detecting drowsiness probability: The algorithm determines the likelihood of drowsiness.

ECG is a low frequency signal; therefore, extracting information from it could potentially take a long time. A healthy person's heartbeat is between 70 to 90 beats per minute (bpm), making it very difficult to extract the ECG peak-to-peak time series signal in a few seconds. Thus, detecting driver drowsiness in real time is a critical issue. To address the challenges mentioned above, and to implement a hardware architecture, developing a robust system is required:

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- Establishing a unique algorithm in few training sets for any specific person.
- Detecting the early sign of drowsiness in as few as 10 to 15 seconds.
- Recording the accuracy of the measurement and self-correction of the algorithm if accuracy drops below certain threshold.

Logistic regression method was implemented to improve the effectiveness of drowsiness detection algorithm. In [21] the authors suggested multilayer neural network using each five peak to peak readings from the ECG. Authors tested ECG data for 6 different sets and obtained 90% accuracy. It has been suggested that by adding more layers to the neural network and collecting more data, the accuracy could be increased. In [25] the authors tested two runs with Naïve Bayes and Support Vector Machine with time-domain features such as average signal over a time period.

This paper is organized as follows: in section II we describe our proposed drowsiness detection system briefly. The new architecture is based on machine learning systems. The system detects drowsiness in approximately less than 20 seconds after the subject starts driving and also maximize the data accuracy at over 90%. Section III details the algorithm that is being employed followed by the conclusion which is the final section.

II. PROPOSED SYSTEM

In this section and followings, we will detail our proposed hardware and machine learning-based algorithm to detect drowsiness. The system is based on heart rate variation time series detection and extracting. According to [19] frequency domain consists of four major intervals, (Ultra-low frequency, very low frequency, low frequency, and high frequency). The low to high frequency ratio drops with drowsiness [18]. Extracting low and high frequencies from a time series using Short Fourier Transform (STFT) is a timely process and accuracy is affected by noise and the algorithm accuracy. Due to the importance of driver mobility, a non-intrusive drowsiness detection system is required. Our proposed system is broken down into three main parts, hardware infrastructure, software design, and algorithm development.

A. Hardware architecture

In the medical field, ECG is a type of electrical signal derived from automatic heart chemical recombination, generating different electrical potential voltages [23]. Usually, these electrical signals are detected with electrodes directly attached to a person's chest. However, for our purposes, it is important that the driver to maintain his or her freedom or mobility and not have any attached sensors or wiring while driving. To this end, Yong [7] suggests placing non-contact ECG sensors on either the seat back or the seat belt of the driver. Additionally, the driver's clothing will be between the sensors and the driver's skin; thus, various types and thicknesses of material will add undesirable noise to the ECG signal. In order to analyze the signal, it is imperative to remove all noise from the ECG signal and derive accurate information from the clean ECG signal, only the data actually generated by the driver's heartbeat. The output from the aforementioned non-contact sensors is a low voltage (mV) signal. Amplifying the signal is necessary for extracting information [19]. In [7] the author suggests that a differential amplifier with two non-contact sensors would increase the gain, as would also adding a feedback technique (DRL). In both ways, the noise effects can be reduced. The feedback technique is implemented by inverting the output of the differential amplifier and connecting it to the driver's body. Also, noise generated by power lines that run alongside some road and major highways must be removed with a notch filter. Since the sensors are non-contact, they generate a lot of noise in a wide range of frequencies, from fractions of a Hertz (Hz) up to one hundred Hz [22]. In this research, we remove both the higher noise frequencies and the DC noise components with hardware filtering. Figure 1 shows different hardware stages in our implementation. In [7] the author suggests using 510 times voltage amplification, five high pass filters, and a 35 Hz low pass filter to remove a majority of this noise. In [9] the authors discuss the placement of sensors around the body of a driver. Different sensor placement around the driver's body generates different levels of noise due to the distance from heart.

In the next step, a combination of micro-controllers and A/D convertors generates a discrete ECG signal and prepares the data for the software stage. Since the signal is low frequency, it is better to use a processor with a low frequency sampling rate. In this experiment, two A/D converters are used. An Arduino with a 10 kHz sampling rate and a Beagle Bone Black with a 200 kHz sampling rate are tested. However, using a higher frequency increases the memory storage size.

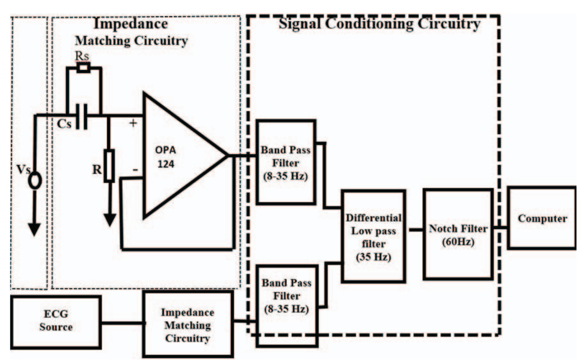

Fig. 1. Hardware design.

B. Software design

The primary focus of software development is to calculate the time series between every two consecutive R complex peaks and then store this data. However, if environmental noise still exists after this process while detecting peak for R complex, particularly in the same HRV frequency range, then the software can pick out a wrong peak, such as S wave instead of the R wave, as demonstrated in Figure 2. Hardware filters help to remove noise in higher frequency ranges and the DC component. However, noise in the same frequency range as HRV survives in the hardware filtering stage. In general, any noise would distort the ECG signal and can affect the peak to peak (RR) readings, erroneously detecting wrong peaks. For example, the S complex could be lifted up and then the next peak reading would be an S complex peak. [4]

In order to clean the ECG signal, we chose the least means square (LMS) adaptive filter method with an LMS algorithm [19]. This method removes the noise within the same frequency range which is mixed with the ECG signal. This algorithm's digital Finite Impulse Response (FIR) filter with adjustable weights filters out all noises with the deepest gradient method [5]. In Figure 3, there are two inputs, discrete function s(n) plus noise n(k) and correlated noise n(k).

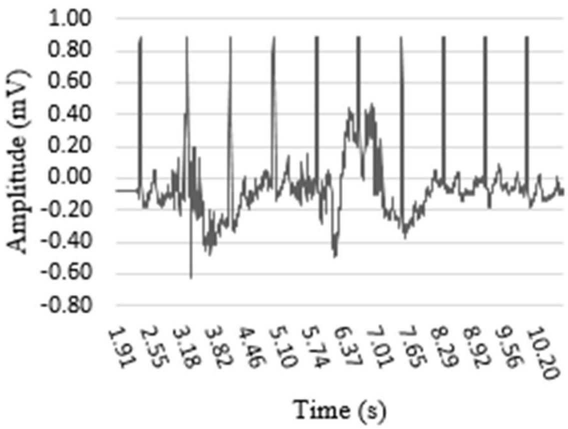

Fig. 2. Squared ECG signal.

The FIR filter adjusts the coefficient filter by applying the deepest gradient method. This method maximizes the correlation between the noise-contaminated ECG signal and environmental noise. The coefficients of the adaptive filter vary with noise which also changes over time. However, we expect a clean ECG signal in e(k) output. LMS algorithm has many advantages over other algorithms such as fast processing since it does not require any squaring, averaging, or differentiating when it minimizes the error in the steepest gradient method [20].

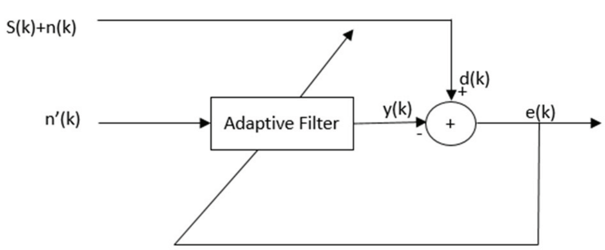

Fig. 3. Adaptive filter (LMS algorithm).

Reading peak-to-peak signals generates a time series with unevenly distributed output over time as shown in Figure 4. In [21] authors proposed a method to increase the accuracy of peak-to-peak reading, the ECG signal is squared which increases R amplitude higher than the other complexes and make it easier to detect R peaks. Due to the fact that heartbeat doesn't follow a regular pattern, the reading is unevenly distributed over time. It is recommended to resample non-uniformity sampled signal [19]. In the resampling process, the data set is re-estimated in equal intervals. Moreover, the resampling method is tied to the Monte Carlo technique in which simulation estimates new data with minimum error [5].

C. Feature Extraction

In [19] authors indicate that HRV frequency domain stores a lot of valuable drowsiness information. In order to extract the R-R time series features in frequency domain, Short Fourier Transform technique was used to slide a window with a variable size and then FFT transformation technique was applied along the times series input. The result is a two dimensional (time- frequency) matrix with R-R time series frequency response. According to the author in [18] the low frequency to high frequency ratio decreases if an individual goes from an awake state to sleep state. Selecting features to achieve the highest machine learning method accuracy is accomplished by trying different features within the same data set. The selected features such as highest peak, standard deviation, and peak-to-RMS value are calculated in the LF and HF zones in the frequency domain. The number of features can be raised by adding other statistical features related to HRV, for example range and skewness of LF and HF in frequency domain have proved to be efficient additions. In [21], the authors suggest that the features in the time domain; such as time variance, peak-to-RMS value, and minimum value; in 25% to 75% of a selected window in time domain. However, adding more attributes from frequency domain could possibly lower the output accuracy, as shown in Figure 5. In this research, many different features in both time and frequency domain, were selected and tested. The final selection, based on the highest output accuracy, are listed in Table 2.

III. ALGORITHM

Since drowsiness has different stages, algorithms relating to likelihood of drowsiness generate a lot of valuable information. We proposed using both the Naïve Bayes method and the logistic regression method in conjunction, because, in both methods, the output value is the probability of drowsiness. However, the logistic regression technique was ultimately favored and chosen over the Naïve Bayes, which has the best result only if the selected features are independent, and this is not the case with the features with which we are working. Furthermore, logistic regression

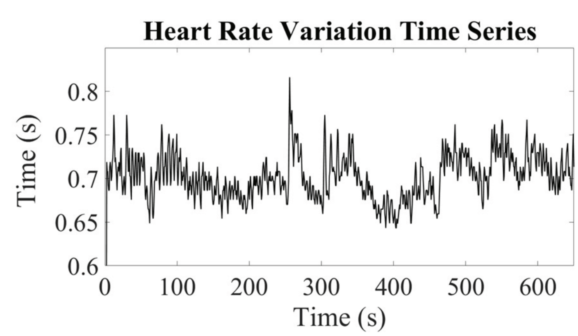

Fig. 4. Peak-to-peak ECG time series.

produces higher accuracy levels than the Naïve Bayes technique does [20].

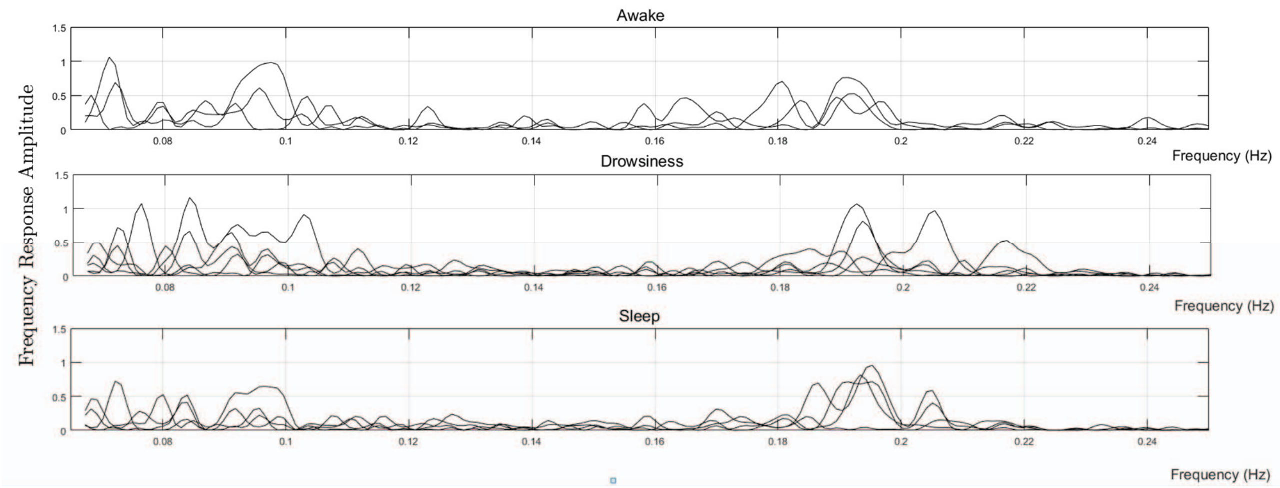

Fig. 5. High and low frequency domain of peak-to-peak time series.

A. Logistic Regression and Prediction of Probability

If we have a set of data in N dimensional space, we define a linear combination of these inputs with arbitrary weight such that

$$s=w^T x$$

and

$$T(s) = \frac{e^s}{1+e^s},$$

where x is the features, w is the extracted weight, and T is the probability output. Linear output, s, is mapped to a different space which is limited between 0 and 1. The variable, S, is called the odds ratio, and it is the product of the logarithmic ratio of the probability of drowsiness and the probability of being awake. This parameter is a linear combination of inputs and is written as: $S=a+\sum b(i)*X$ where a(Intercept) and b(i) are generated by the algorithm, and X is the input matrix. In this case, learning the exact algorithm is achieved with minimal error with a probability function defined as

$$p(y|x)=\theta(yw^T x),$$

where y is extreme drowsiness and is assigned a value of +1. Two deep sleep and awake states are being assigned the values +1 and 0. The likelihood of each state is defined by the probability function $p(y|x)$. In cases where there are multiple data sets, there are n sets, where

$$(x_1, y_1)\ldots(x_N, y_N),$$

which are independent measurements. Therefore, the likelihood of the total measurement is the multiplication of each individual data set measurement defined as

$$\prod p(y_n|x_n).$$

In order to maximize the likelihood, the inverse logarithm is differentiated with respect to x(n), and the results evaluates the coefficients and also non-linearity function in the logistic regression method [20]. Linear regression avoids overfitting errors with elimination of large coefficients in linear stage and mapping all outputs to an interval, the number of independent experiments increases the accuracy of the algorithm. Figure 6 summarizes the process of drowsiness detection from the start of recording the driver's ECG data, through the data processing, and ending with the determination of the driver's state of drowsiness.

Algorithm 1: To detect HRV and for making the decision between drowsy and non-drowsy state

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Input: Read ECG Signal (from two different sensors)
Output: The likelihood of drowsiness
// read normalized ECG signal
ECG_signal = normalized (ECG)
// filtering the ECG signal
Filtered_ECG = adaptiveLMS (ECG_signal)
// defining the sampling rate
Fs = samplingRate
/* calculate time interval between R peak to peak */
R_to_R = HRV (Fs, Filtered_ECG)
// resampling time series
RR = resamplingHRV (R_to_R)
// extracting frequency domain features
f-features = freqAnalysis (RR)
/* f-features:
f1 = absolute magnitude square of Short Fourier Transform
f2, f3 = peak magnitude frequency response
f4, f5 = standard deviation
f6 = peak to RMS ratio
f7 = high magnitude frequency response
/* *f-features*
// extracting time domain features
t-features = timeAnalysis (RR)
/* t-features:
t1 = average signal in every 64 points
t2 = RMS signal of 64 points window
t3 = standard deviation in every 64 points
/* *t-features*
//creating instances for logistic regression
Instances (:) = createInstance (f-features, t-features)
//creating data for logistic regression

```
TotalData(:) =[Instances (:),Label(:)]
//splitting data for training and testing
Training Data = 90% TotalData
Testing Data = 10% TotalData
// calculating intercept and model's coefficient//...
B(:)=logistic_regression(TrainingData(:))
//  calculating odds for a new set of data //
Logit (:)=B(0)+sum(B*Test Data)
// Output: Probability of drowsiness //
Probability(:) =inverse(1+exp(-logit(:)))
```

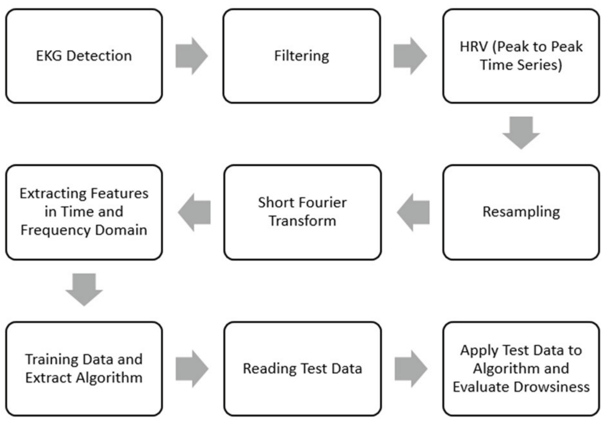

Fig. 6. Flow chart of drowsiness detection and details about algorithm 1 implementation.

B. Experiment

We developed a hardware system with two different setups, one with contact sensors and one with non-contact sensors. In order to detect the ECG signal, remove unwanted noise, and also gain the sensor ECG output, we tested two different micro-controllers, Beagle Bone Black and Arduino. We collected ECG signal data using each device for a five-hour period that included the subject's transition from being awake to being asleep. That was converted to discrete data. The Arduino's sampling frequency of 10 kHz was much lower than that of the Beagle Bone Black, 200 MHz; so, the data took up much less space and sped up the system performance. The program was developed in Matlab 2015.

The ECG data were collected from three different individuals of different ages and genders, and the system was tested with two different methods, logistic regression and Naïve Bayes. The result turns out to have higher accuracy in case of logistic regression. Since Naïve Bayes method relies on independent features and our features are dependent in frequency domain, therefore, the result confirms the lower accuracy of Naïve Bayes output. The accuracy of output for logistic regression test is over 92%, however, Naïve Bayes accuracy never exceeds 85% accuracy. Moreover, the minimum time of drowsiness detection in our set-up was 12-24 seconds. For every new person, the system collects few sets of ECG data while the subject is asleep, and train the data to create a unique algorithm for each person. In the testing mode, the system detects between 12 and 24 seconds of ECG signal and immediately publishes its prediction as the probability of drowsiness, as illustrated in Figure 7. The experiments result for three people shows a consistent accuracy over 90% in less than 24 seconds. Our developed algorithm provides steady results over time detecting drowsiness (approximately 20 seconds detection). The algorithm and feature extraction are listed in Tables I and II.

TABLE I
TIME TO DETECT DROWSINESS USING MACHINE LEARNING SYSTEM

Time	Machine Learning	Subj. 1	Subj. 2	Subj. 3
Delay to detect (s)	Yes	28	24	30
Delay to detect (s)	No	145	138	132

TABLE II
COEFFICIENT OF LOGISTIC REGRESSION ANALYSIS

Subject	Subject 1	Subject 2	Subject 3
Window_mean	1868	1734	1441
Window_std	619.4	589.2	673
Window_rms	-1496.5	-1567.2	-1460
Peak High Freq	112	132	150.5
Peak Low Freq	6.4	7.2	14.29
Std_HF	-80.1	-74.4	-82.6
Std_LF	-59.4	-68.2	-10.36
Peak2rmsHf	-4.5	-5	-7.16
Peak2rmsLF	-3.4	-3.2	-9.85
Intercept	-272.0	-293	-199.83

IV. CONCLUSION

In this paper, we examined HRV to detect driver drowsiness. The accuracy was over 90% with minimum window of 20 seconds (ECG signal). Multiple tests were performed with data comprising of different age or gender. Study also confirms the importance of low frequency (0.05 Hz – 0.1 Hz) and high frequency (0.16Hz-0.2Hz) areas. It also reveals that ultra-lower band ULF and VLF do not carry important information for drowsiness detection. Logistic regression provided 90% accuracy, however, accuracy can be improved if more training data regarding different psychological states of driver is collected. Also, extracting more independent features from frequency domain leads to higher accuracy and it even makes Naïve Bayes method more attractive than the logistic regression method.

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