Real-time Sleep Prediction Algorithm using Commercial Off the Shelf Wearable Devices

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***Abstract*—As reported by the American National Highway Traffic Safety Administration (NHTSA), sleep while driving is one of the most influential factors in fatal vehicle crashes, along with excessive vehicle speed and alcohol consumption. Physiologically speaking, driving for more than two hours in a nocturnal environment produces a driving impairment like a blood alcohol concentration of 0.05%. In this work, we present an innovative and patented sleep prediction method based on the analysis of the Autonomic Nervous System (ANS) (and its subsystems) that monitors the actions happening during the transition from awake to sleep onset. The prediction method processes the Heart Rate (HR) and the Heart Rate Variability (HRV) as collected by a wearable device on the subject wrist. Using a sliding window approach that operates on 20 seconds of samples (acquired at 1 Hz), the trend of the variance of HR and HRV is used to classify the subject condition according to a reduced Karolinska Sleepiness Scale (rKSS) that comprises five stages: Calibration, Awake, Low Drowsiness level, Medium Drowsiness level, High Drowsiness level. The prediction method has been validated experimentally using a set of recordings acquired in a realistic environment (AVL dynamic car simulator, in Graz (AT)). During the experiments, 15 subjects performed several rounds of the Maintenance Wakefulness Test (MWT). Each subject was equipped with a wearable device and apolysomnography medical equipment to gather both the data processed by the proposed approach, and the data set that constituted the ground truth under the supervision of a sleep expert medical doctor. A further experimental section has been conducted, involving the Italian truck company Chrono Express. 15 different drivers have utilized the built-up system for more than 13000 km. The proposed method is sensor agnostic, as it has been proven through preliminary activities with contactless Radio Frequency (RF) sensors. The output produced by the proposed method and the sleep scoring performed by the sleep expert medical doctor during the first experimental section were compared. The first sleep onset event showed an accuracy of 93.3%, a sensibility of 95% and a sensitivity of 100%. Instead, regarding the following sleep onset events an accuracy of 86.66%, a specificity of 66.67%, and a sensitivity of 95.24% were calculated.**

***Index Terms*—IOT, Rule-based algorithm, Drowsiness, Sleep, Heart Rate Variability, Heart Rate, Physiological data, Real-time.**

This work has been carried out in cooperation with Sleep Advice Technologies S.r.l. (https://www.satechnology.eu/)

I. Introduction

The growing interest in techniques that can accurately identify when drivers lose attention due to distraction or health issues has led to the development of a range of approaches and solutions. One potential approach is prevention, by means of sleep exams to assess sleep quality and identify potential health problems that may affect a person's ability to stay alert while driving. This can help to prevent accidents and ensure that drivers are fit to operate a vehicle. Another approach is protection, which involves predicting when sleep is likely to occur based on certain physiological behaviors. This can help to alert drivers and prevent them from falling asleep at the wheel, which can be particularly dangerous on long journeys or in monotonous driving conditions. One common test used in the field of sleep medicine to assess sleep quality and identify potential health problems is polysomnography (PSG) [1], a multiparameter test that involves the use of a range of sensors to gather data about behavioral states during the sleep of a subject. It exploits electroencephalogram (EEG) to measure brain activity, photoplethysmograph (PPG) to measure blood flow, electrocardiogram (EKG) to measure heart rate, electrooculogram (EOG) to measure eye movement, electromyogram (EMG) to measure muscle activity, nasal cannula to measure breathing, and thoracic and abdominal bands to measure chest and abdominal movement. One specific exam for evaluating the excessive sleepiness is the Maintenance of Wakefulness Test (MWT) [2], which has been approved and validated by the American Academy of Sleep Medicine (AASM). The MWT involves placing a subject in a soporific environment and monitoring its ability to stay awake exploiting a subset of the sensors involved in a PSG. The data collected during the MWT is then analyzed by a sleep expert, who follows specific AASM rules to classify if the person is sleeping or not. For instance, the transition between wakefulness and non-rapid eye movement (NREM) stage 1 can be identified based on the presence of low-amplitude, mixed-frequency activity and vertex sharp waves in the EEG, and slow eye movements in the EOG. While the use of such a large number of sensors is not practical in a car setting, there are a range of alternative solutions that can be exploited to assess driver drowsiness and alertness. These include:

- Vehicle-based measurements such as speed, acceleration, and wheel position, which can provide an indication of a driver's alertness and reaction times. However, these measurements are dependent on a range of factors , including the driver's skill level, road conditions, and vehicle characteristics, and may not always provide a reliable indication of drowsiness. [3], [4]
- Behavioral analysis of the driver's eye state, blinking, yawning, and head movement can also provide useful information about the level of alertness of a subject. These measurements can be gathered using cameras or other sensors , which are relatively easy to use. However, they can be affected by factors such as camera movement, lighting conditions, and the presence of sunglasses. Thus, accurate results are not always provided. [5], [6], [7]
- Physiological measurements based on biometric signals such as heart rate, brain activity, and respiration can also be analyzed to assess driver drowsiness. [8], [9], [10]

Razman et al. published a survey that that compared these three. The relevant point of the survey is that the physiological measurements is even most accurate in all the different scenarios that they took in consideration.
The physiological measurements are based on the analysis of the autonomic nervous system (ANS) and its subsystems, including the parasympathetic nervous system (PSNS) and the sympathetic nervous system (SNS). The PSNS is often referred to as the "rest and digestion" or inhibitory system, while the SNS is referred to as the "fight or flight" or excitatory system. Several studies have focused on the analysis of physiological signals to assess driver drowsiness. Particularly, some works exploited photoplethysmograph (PPG) signals to calculate heart rate variability (HRV) as a measure of sleep classification. There are two main types of HRV that are commonly identified in the literature: peak-to-peak distance, which is based on the time between consecutive heartbeat peaks in the electrocardiogram (EKG) or PPG; and the LF/HF ratio, which is based on the power spectrum of the PPG (or EKG). [12]
The current study aims to develop an algorithm that can predict sleep onset by analyzing real-time HRV and heart rate (HR) data extrapolated from the time domain. By monitoring these physiological signals and analyzing the activity of the ANS, it may be possible to identify patterns that indicate an increased risk of sleep onset and trigger an alert to prevent accidents. Moreover, the proposed algorithm aims to provide a more portable and practical solution for monitoring driver alertness and predicting sleep onset in real-time. By analyzing HRV and HR, it may be possible to identify patterns that indicate an increased risk of sleep onset and trigger an alert to prevent accidents. Overall, the use of physiological measurements such as HR and HRV has the potential to provide a reliable and accurate way to assess driver drowsiness and alertness and to prevent accidents caused by driver fatigue or inattention. One of the key challenges in developing an effective drowsiness detection algorithm is the need to account for a wide range of factors that can affect a person's level of alertness. These can include physical and mental fatigue, boredom, stress, illness, and using medications or other substances that can impair cognitive function. To accurately predict sleep onset, it is important to consider these factors and how they may impact the physiological signals being monitored. Another challenge is the need to ensure that the algorithm is reliable and accurate under various conditions. For instance, the algorithm should be able to accurately detect drowsiness in drivers driving on long journeys, in monotonous conditions, or in challenging weather conditions. It should also be able to handle variations in the quality of the physiological signals being monitored and be robust enough to handle noise or interference that may be present in the data. Overall, the development of a reliable and accurate drowsiness detection algorithm has the potential to significantly improve road safety and reduce the number of accidents caused by driver fatigue or inattention. By predicting sleep onset and alerting drivers to the need to rest or take a break, it may be possible to prevent accidents and save lives. The designed real-time sleep prediction algorithm was based on medical observation by mapping the ANS behavior. The algorithm underwent thorough testing in a realistic environment to validate its effectiveness and was compared against the gold standard Polysomnography exam. The study leveraged data obtained from a readily available commercial wearable device, which served as the primary data source for algorithm development. Finally, the algorithm was successfully incorporated into an Android application, enabling practical implementation and widespread usage.

II. Dataset

This study was conducted analyzing recordings obtained in a realistic environment (AVL dynamic car simulator in Graz, Austria) during MWT with a group of healthy adult subjects. A total of 15 subjects (11 males and 4 females) aged 21 to 60 years (average age of 45 years) participated in the study and were equipped with state-of-the-art PSG device. A sleep expert medical doctor analyzed the full polysomnography data and identified the sleep onset epoch (i.e., the "ground truth" of the method). The subjects have been asked to drive, in a highway driving scenario, for at least 1 hour. In addition, the subjects wore Garmin VenuSq smartwatches, which processed signals to calculate HR, HRV, Respiration Rate (RR), and oxygen saturation (SpO2). The smartwatch then transmitted these variables to a smartphone via Bluetooth Low Energy (BLE), and the smartphone provided real-time feedback to the user on their status. The smartphone could also send data and driver status reports to a server using the MQTT protocol (as shown in Figure 1). The AVL dynamic car simulator in Graz, Austria is depicted in Figure 2.

III. Drowsiness Detection Algorithm

The drowsiness detection algorithm was developed and tested by means of MATLAB. The algorithm processed HR and HRV with a sampling frequency of 1 Hz, which were

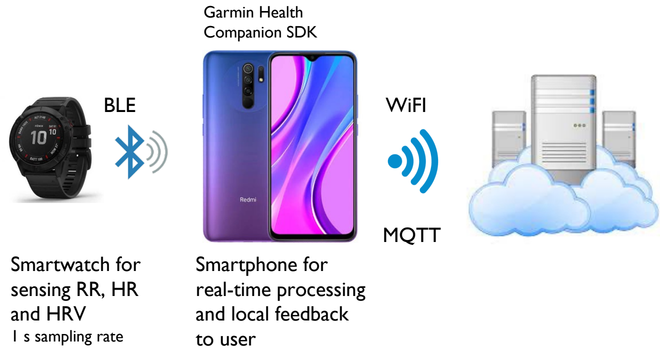

Fig. 1. Built System Representation.

Fig. 2. AVL dynamic simulator, Graz (AT).

collected exploiting a Garmin smartwatch. The output about the driver's condition was generated according to the reduced Karolinska Sleepiness Scale (rKKS) and was constituted of five stages: Calibration, Awake, Low Drowsiness level, Medium Drowsiness level, High Drowsiness level. [13] The algorithm worked in real-time, so processed the collected variables as overlapping windows of n samples. The window size has been selected by the observation of medical doctor. The medical doctor found that, by monitoring certain time periods of cardio-respiratory parameters, it is possible to identify specific levels of sleepiness. The real-time algorithm run as shown in the Pseudo-code 1.

IV. Results

The algorithm was validated using data collected from a dynamic simulator through 15 MWT tests with a diverse group of participants of different genders and ages. A total of 21 sleep onset events were recorded and scored by a medical doctor. The dataset was analyzed according to the study of Zhu et al. [14]. Resulting in 20 true positives (TP), 6 true negatives (TN), 3 false positives (FP), and 1 false negative (FN). This led to a sensitivity of 95.24%, a specificity of 66.67%, and an accuracy of 86.66%, where:

Algorithm 1 Drowsiness Detection Algorithm

```
START
while there is signal do
  Collect n samples of HR and HRV and store in vectors HRi and HRVi
  if n samples are collected then
    Normalize the HRV values by calculating the scalar product of each HRV value with its corresponding HR value. Save the resulting normalized values in the vector Din
    Calculate standard deviation of Din and save result in vector DinSD
    if N DinSD are calculated then
      if First time then
        Calculate average of first derivative of DinSD and save result in Tm
        return rKSS0: Calibration;
      else
        The windows HR, HRV, Din and DinSD slide in time discarding oldest value and adding new value
        Calculate first derivative of DinSD and save result in dDinSD
        count = 0
        DOD = 0
        for i = 1 to i = WindowSize-1 do
          if dDinSD[i]¡Tm then
            count++
          else
            count = 0
          end if
          if count > DOD then
            DOD = count
          end if
        end for
        if DOD <= WindowSize * 0.5 then
          return rKSS1: Awake;
        end if
        if DOD <= WindowSize * 0.65 and DOD > WindowSize * 0.5 then
          return rKSS2: Low Drowsiness Level;
        end if
        if DOD <= WindowSize * 0.80 and DOD > WindowSize * 0.65 then
          return rKSS3: Medium Drowsiness level;
        end if
        if DOD > WindowSize * 0.8 then
          return rKSS4: High Drowsiness level;
        end if
      end if
    end if
  end if
end while=0
```

- Sensitivity = TP/(TP + FN)
- Specificity = TN/(TN + FP)
- Accuracy = (TN + TP)/(TN+TP+FN+FP)

When considering only the first sleep onset event for each participant, the sensitivity, specificity, and accuracy are 100%, 95%, and 93.3%, respectively. Table I shows the first sleep onset epoch and the first alarm generated for each participant. A second experimental activity has been conducted to test the system in a real scenario. This second experimental activity has been conducted in order to test both, the drowsiness detection algorithm and the developed Android application (Fig. 3).

TABLE I
MEDICAL DOCTOR SLEEP DETECTION EPOCH AND THE SLEEP ONSET PREDICTION EPOCH

Participants	**Ground Truth Sleep Detection**	**Algorithm Drowsiness Detection**
a	15:15:05	15:09:42
b	17:30:35	17:28:06
c	11:40:38	11:35:10
f	14:09:35	13:53:50
g	13:16:35	13:14:03
h	None	11:12:34
m	14:36:00	14:34:32
n	16:33:00	16:25:43
q	12:43:00	12:18:58

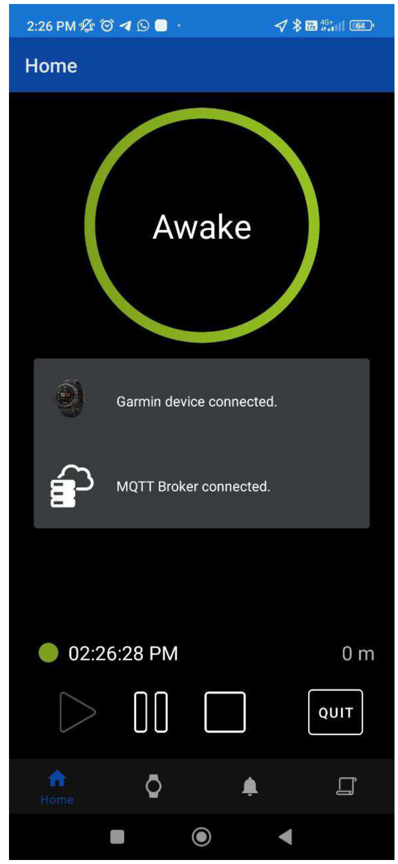

Fig. 3. Developed Android application.

Chrono Express truck drivers tested the system for approximately 43 days, 24h per day, driving more than 13000 km. For evaluating the system's effectiveness, the alarms density has been estimated in certain time areas:

- Night is the time slide between 9 pm and 6 am the following day.
- Nap includes the time slots that are more likely for people to fall asleep (10 am - 11 am, 3 pm - 4 pm, 6 pm -7 pm).
- Day, which refers to the remaining time slots during the day.

Thus, the alarm density has been calculated as the total number of alarms divided by the total number of hours for each time area:

- Night = 0.1876 Alarms/Hour
- Nap = 0.0408 Alarms/Hour
- Day = 0.0261 Alarms/Hour

Also, this activity enhanced the system's effectiveness due to the difference in alarm density.

V. Conclusions

This research aimed to develop an algorithm that can predict the onset of sleep using data from commercial devices without needing access to raw sensor data (i.e., PPG or EKG). The first experimental activity showed that the method is effective for the first sleep onset event and subsequent ones, indicating good system inertia. The second one enhanced the system's effectiveness by reporting an important alarm density above the different time slots. A smartphone app has also been developed to provide a user-friendly interface for interacting with the driver in case of a potential critical drowsiness state. Importantly, the proposed method is not reliant on specific sensors, as demonstrated through initial testing with contactless RF sensors.

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