Fuzzy-Logic Inference for Early Detection of Sleep Onset in Car Driver

Mario Malcangi[1,*] and Salvatore Smirne[2]

[1] DICo - Dipartimento di Informatica e Comunicazione,
[2] Dipartimento di Tecnologie per la Salute
Università degli Studi di Milano
Milano - Italy
{mario.malcangi,salvatore.smirne}@unimi.it

Abstract. Heart rate variability (HRV) is an important sign because it reflects the activity of the autonomic nervous system (ANS), which controls most of the physiological activity of the subjects, including sleep. The balance between the sympathetic and parasympathetic branches of the nervous system is an effective indicator of heart rhythm and, indirectly, heart rhythm is related to a patient's state of wakefulness or sleep. In this paper we present a research that models a fuzzy logic inference engine for early detection of the onset of sleep in people driving a car or a public transportation vehicle. ANS activity reflected in the HRV signal is measured by electrocardiogram (ECG). Power spectrum density (PSD) is computed from the HRV signal and ANS frequency activity is then measured. Crisp measurements such as very low, low, and high HRV and low-to-high frequency ratio variability are fuzzified and evaluated by a set of fuzzy-logic rules that make inferences about the onset of sleep in automobile drivers. An experimental test environment has been developed to evaluate this method and its effectiveness.

Keywords: onset sleep, heart rate variability, power spectrum density, fuzzy logic, autonomic nervous system.

1 Introduction

Falling asleep at the wheel is a cause of very dangerous accidents, so many methods have been investigated to find a practical solution for early detection of the onset of sleep to achieve an higher level of safety in private and public transportation systems.

To detect sleep onset early, continuous monitoring of the driver's physiological state needs to be carried out. The electrocardiogram (ECG) carries most of the information about physiological status.

Capturing an ECG is a complex task that requires the accurate application of several electrodes to the patient. This may be feasible in a clinical context, but is not practical for a person driving a car. A non-invasive method for capturing ECG signal needs to

[*] Corresponding author.

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be developed for practical application to monitoring a driver's physiological status in the automobile environment [1] [2].

Other physiological information can be monitored along with the ECG, such as eye movements, breathing rate, muscular tone, and arm movements. This additional information can also be captured with non-invasive methods, so that a very robust and effective set of features can be measured.

Such information is highly fuzzy, so a smart inference system is needed to infer about sleep onset. The fuzzy-logic-based inference system can be very effective if several physiological features concur in the decision, but a practical system for early detection of oncoming driver sleep onset can also be based also on EEG measurements alone. This is because there is enough information in the EEG signal directly related to sleep-wake control [3] [4].

Sleep is a physiological state characterized by variations in the activity of the autonomic nervous system that is reflected in heart rate and its variability (HRV). The power spectral density (PSD) of heart rate varies with the change from wakefulness to sleep [5] [6]. The low-to-high frequency ratio is a valid indicator of such change because it reflects the balancing action of the sympathetic nervous system and parasympathetic nervous system branches of the autonomic nervous system.

When the activity of the sympathetic nervous system increases, the parasympathetic nervous system diminishes its activity, causing an acceleration of cardiac rhythm (shorter beat intervals). Cardiac rhythm deceleration is caused by low activity of the sympathetic nervous system and increased parasympathetic nervous system activity, producing a deceleration of the heart rhythm (longer beat intervals).

The PSD of HRV (Fig. 1) signal shows that sympathetic activity is associated with the low frequency range (0.04–0.15 Hz) while parasympathetic activity is associated with the higher frequency range (0.15–0.4 Hz). Because the frequency ranges of sympathetic and parasympathetic activity are distinct, it is possible to separate the sympathetic and parasympathetic contributions.

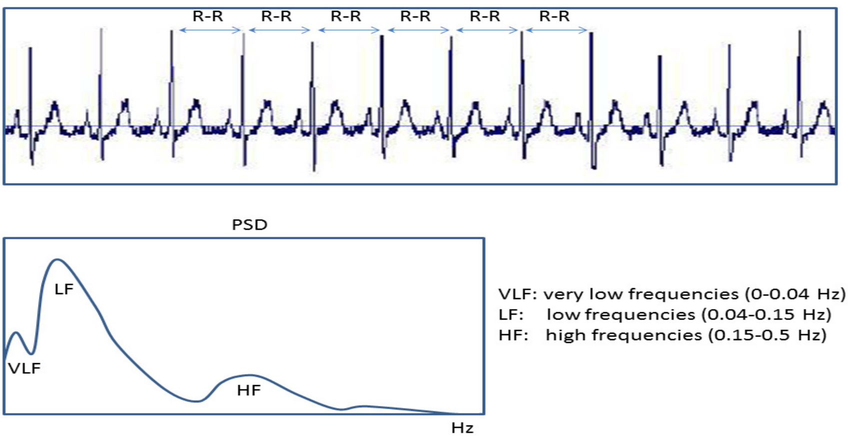

Fig. 1. Very low, low and high frequencies in power spectrum density (PSD), computed from the heart rate variability signal (HRV)

The PSD analysis of beat-to-beat HRV provides a useful means for understanding when sleep is setting in. Sleep and wakefulness are directly related to the autonomous nervous system [7]. In the awake state, the low-frequency spectral component (sympathetic modulation activity) was significantly higher and the high-frequency spectral components (parasympathetic modulation activity) significantly lower. Conversely, in the asleep state, the low-frequency spectral component (sympathetic modulation activity) was significantly lower and the high frequency spectral components (parasympathetic modulation activity) significantly higher. If we consider the balance of low frequency versus high frequency in a person's PSD, it is possible to predict the onset of falling asleep.

A set of experiments demonstrates that, when a person tries to resist falling asleep, the LF/HF ratio of PDS computed from the HRV signal increases significantly a few minutes before becoming significantly lower during the sleep stage. Like a reaction to falling asleep, it causes high activity of the sympathetic system while the parasympathetic system decreases its activity.

Making inferences about physiological status from the HRV signal is very difficult because of the high degree of variability and the presence of artifacts. Softcomputing methods can be very effective for inferring in such a context [8].

There are several methods [9] [10] [11] for performing predictions with artificial neural networks (ANN). Mager [12] utilizes Kohonen's self-organizing map (SOM) to provide a method of clustering subjects with similar features. This method, applied to the problem of detecting oncoming sleep early, allows artifacts to be filtered and the variability component of noise combined with the primary HRV signal to be smoothed.

The drawback is that ANNs are very difficult to train for HRV of normal subjects who fall asleep at the wheel, because it is difficult to detect precisely the time when the event happens.

An alternative approach uses fuzzy decision logic [13] [14] to model the oncoming onset of sleep. Such an approach is effective because it allows use of the membership function to model data features and of a sleep-disease specialist's ability to interpret the PSD LF/HF ratio dynamics as an index of oncoming onset of sleep.

2 System Framework

The whole system consists of a signal acquisition and preprocessing subsystem, a feature extraction subsystem, and a fuzzy-based decision logic module (Fig. 2).

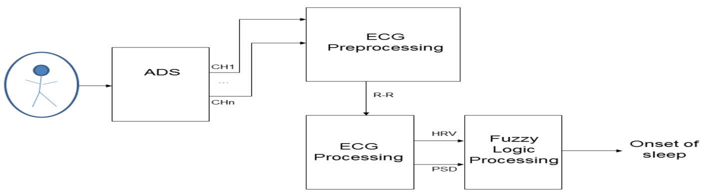

Fig. 2. System architecture consists of an Analog-to-Digital Subsystem (ADS), an ECG preprocessing subsystem, an ECG processing subsystem, and a fuzzy logic processing engine

ECG signal acquisition is not a simple task because noise and artifacts are very strong (Fig. 3). Good signal acquisition can be assured by a high-quality, analog-to-digital subsystem (ADS), specifically designed for ECG signals.

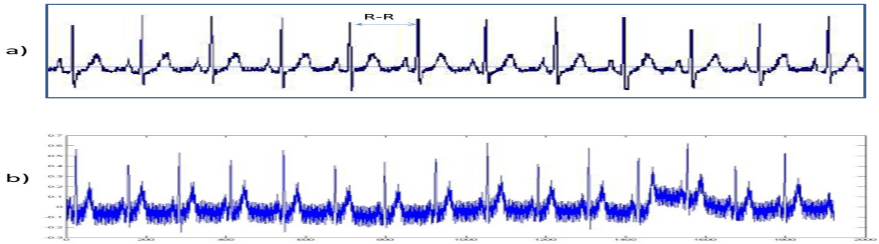

Fig. 3. ECG signal acquired at thorax level (a) and at hand level (b)

The ECG signal is sampled at 500 samples per second (SPS) with a depth of 24 bits.

A set of signal-processing algorithms was applied to the acquired ECG signal to remove noise and artifacts, so that the QRS complex can be detected (Fig. 4). The ECG is filtered to remove 60-Hz noise, baseline fluctuations, and muscle noise.

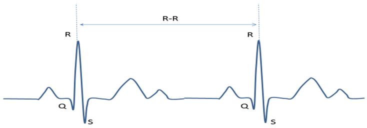

Fig. 4. The QRS complex and R-R interval

Baseline oscillations are removed using a zero phase fourth-order, high-pass filter (1-Hz cutoff frequency).

2.1 ECG Processing

To compute the HRV signal, the heartbeat needs to be extracted from the acquired ECG signal. This is bandpass filtered (centered at 17 Hz), so the QRS complex will be extracted from the captured ECG signal. To emphasize it, the following derivative filter is applied:

$$y(n) = x(n) - x(n-1) \tag{1}$$

followed by an eight-order, low-pass Butterword filter (cutoff frequency at 30 Hz) [15].

The QRS complex is now ready to be thresholded and measured for peak-to-peak period (R-R interval). This is done by squaring the sample values and passing them through the following moving average filter [15]:

$$y(n) = \frac{1}{N}\sum_{i=0}^{N-1} x(n-i) \tag{2}$$

2.2 HRV and PSD Computation

HRV is computed from the R-R intervals. These are measured and collected as a series of times. Because it is an irregular interval-time sequence, it needs to be converted into a uniformly sampled time-spaced sequence.

PSD distribution is then computed so that measurements on the following three frequency bands can be carried out:

- very low frequencies (0-0.04 Hz)
- low frequencies (0.04-0.15 Hz)
- high frequencies (0.15-0.5 Hz)

The low-to-high frequency ratio is also computed.

2.3 Fuzzy Decision Logic

A fuzzy logic engine (Fig. 5) was tuned to make inferences about sleep-onset events. The fuzzy engine makes epoch-by-epoch (20 or 60 seconds per epoch) inferences. HRV and PSD features are fed to the engine in a fuzzified form.

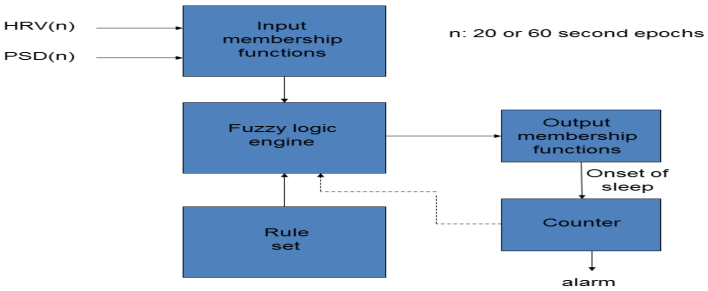

Fig. 5. Fuzzy-logic decision engine tuned to predict the onset of sleep in drivers

To fuzzify such features, a set of membership functions are derived from the distribution of the crisp values in the respective measurement domains (Fig. 6).

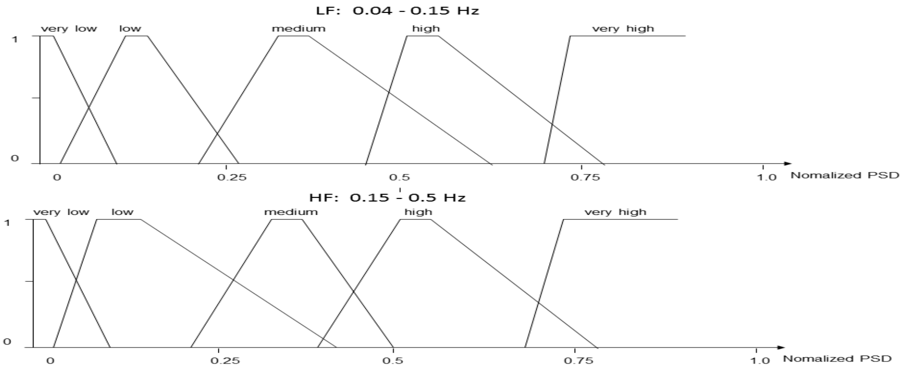

Fig. 6. Membership functions to fuzzify input features

A set of rules has been defined and tuned manually to achieve the best performance for the decision logic. The fuzzy rules looks like this:

if HRV(n) is Low and
LF(n) is Medium Low and
HF(n) is Medium High and
LF/HF is Medium
then the epoch is ONSET_SLEEP

. . .
if HRV(n) is High and
LF(n) is High and
HF(n) is Low and
LF/HF is High
then the epoch is WAKE

. . .
if HRV(n) is Low and
LF(n) is Low and
HF(n) is High and
LF/HF is Low
then the epoch is SLEEP

These three rules are the strongest in determining the output for ONSET_SLEEP, WAKE, and SLEEP states. There are more variants of these rules are in the rule set, each generated during tuning to correct for false detectios that have occurred due to noise and artifacts.

The output of the fuzzy-logic engine consists of a set of singleton membership functions (Fig. 7). The “center of gravity” algorithm is applied to defuzzify the final decision:

$$\text{crisp\_output} = \frac{\sum(\text{fuzzy\_output})\, x\, (\text{singletonposition})}{\sum \text{fuzzy\_output}}$$

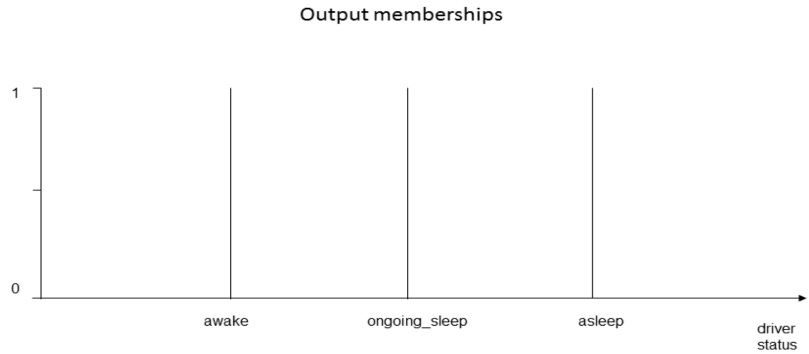

Fig. 7. Singleton membership function to defuzzify the final decision

An output module counts how many times a short epoch (20 seconds) has been classified as ONSET_SLEEP and how many long epochs (60 seconds) are classified as SLEEP. Such counts are used as a feedback (memory) to the inference engine, as well as to integrate the epoch-by-epoch outputs of the fuzzy-logic engine.

3 Experimental Results

A MATLAB-based application (Fig. 8) was developed to conduct experimental tests. This environment was connected to an ECG acquisition board (Fig. 9) so that bioelectrical signals are captured at the thorax or arm level.

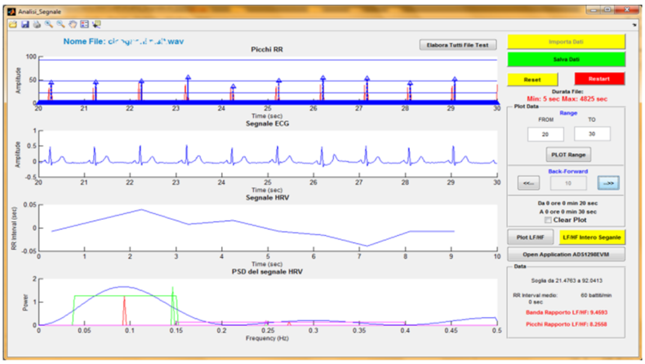

Fig. 8. MATLAB-based application developed to host the experiments

Two sets of experimental tests were carried out. The first set used ECGs acquired in a clinical context (thorax). The second refers to ECGs acquired in a field context (hands). This signal is noisy and less well-defined in QRS complex However, after more rules are added, sleep-onset detection showed the same detection rate as clinically collected data (90% true detection on a set of 10 analyzed ECG).

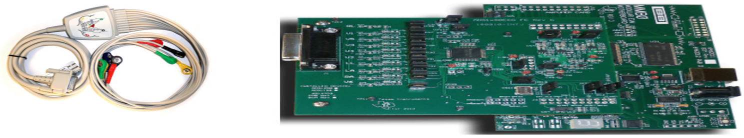

Fig. 9. Analog-to-digital acquisition board and cable connector to capture EEG signal

The results of both experiments (Fig. 10) confirmed our thesis that the sleep onset can be predicted by using features extracted only from the HRV signal (clinical data). The experiments also confirmed that sleep-onset detection may be successfully based on the analysis of an ECG signal captured from the driver's hands.

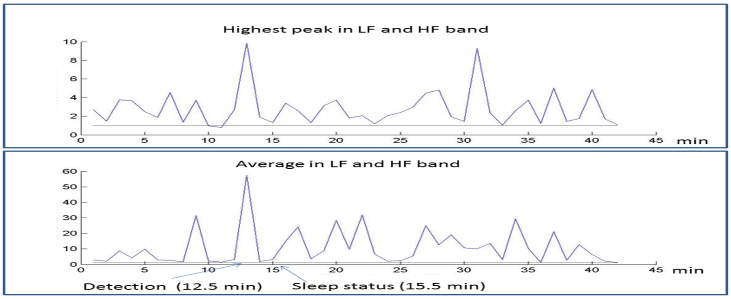

Fig. 10. One early detected sleep onset

4 Conclusion

Early detection of oncoming sleep can be based on the capture and processing of an ECG signal from a non-invasive procedure. The HRV signal proves to be a good carrier of information related to sleep onset. The balance of low to high frequencies of the PSD calculated from the HRV signal can be fuzzily processed to detect the early signs of falling asleep. More improvements in such a detection system can be achieved by using an additional non-invasive technique to capture and process some other signal, such as breathing rate or arm movement.

Compared to non-HRV measurement-based methods, the proposed method has several advantages, mainly that it is non-invasive and based on neurological information rather than on visual signs (eyes movements) or gestures (head movements).

The fuzzy-logic method proves to be the most appropriate way to make inferences based on HRV information, because its main features are relative power reading at different frequencies. These features can easily mapped onto membership functions and compiled into fuzzy rules by using an expert's knowledge, i.e. that of a physician who is expert in sleep disorders).

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