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Detection of microsleep events in a car driving simulation study using electrocardiographic features

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Abstract: Microsleep events (MSE) are short intrusions of sleep under the demand of sustained attention. They can impose a major threat to safety while driving a car and are considered one of the most significant causes of traffic accidents. Driver's fatigue and MSE account for up to 20% of all car crashes in Europe and at least 100,000 accidents in the US every year. Unfortunately, there is not a standardized test developed to quantify the degree of vigilance of a driver. To account for this problem, different approaches based on biosignal analysis have been studied in the past. In this paper, we investigate an electrocardiographic-based detection of MSE using morphological and rhythmical features. 14 records from a car driving simulation study with a high incidence of MSE were analyzed and the behavior of the ECG features before and after an MSE in relation to reference baseline values (without drowsiness) were investigated. The results show that MSE cannot be detected (or predicted) using only the ECG. However, in the presence of MSE, the rhythmical and morphological features were observed to be significantly different than the ones calculated for the reference signal without sleepiness. In particular, when MSE were present, the heart rate diminished while the heart rate variability increased. Time distances between P wave and R peak, and R peak and T wave and their dispersion increased also. This demonstrates a noticeable change of the autonomous regulation of the heart. In future, the ECG parameter could be used as a surrogate measure of fatigue.

Keywords: ECG; electrocardiogram; heart rate variability; HRV; microsleep event; MSE; wave morphology.

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1 Introduction

Microsleep events (MSE) are short periods of sleep that can last from a fraction of a second to several seconds and can become extremely dangerous while driving a car. They are one of the most common causes of traffic accidents. In Europe, recent studies have shown that up to 20% of all crashes on the road are related to driver's fatigue, while in the US more than 100,000 automobile crashes annually are driven by MSE. Furthermore, in the transport industry, diminished vigilance is the main cause of truck crashes and around 60% of all fatal causalities. Thus, the prevention of such accidents has become a relevant problem to society [1].

Since fatigue and drowsiness have a severe impact on the driver's level of concentration, reaction time, memory and driving performance, it has been observed that physiological parameters are modified when sleepiness appears. However, in contrast to the well-known alcoholic tests, there is no equivalent, forensically valid test for sleepiness. For this reason, other approaches based on biosignal analysis are being used to quantify the degree of vigilance of a driver. The main goal is to alert the driver when he is not sufficiently aware of the situation and thus prevent an accident [2].

In this paper, we hypothesize that an electrocardiogram- (ECG) based analysis can be developed to detect an MSE. For this purpose, we developed a large variety of rhythmical and morphological features and investigated the behavior of those before and after an MSE in relation to reference baseline values without sleepiness. We evaluated the discriminating power of the ECG-based descriptors using recordings from a car driving simulation study.

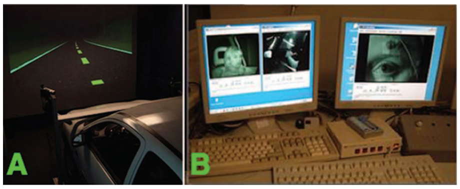

Figure 1: Laboratory used for MSE study.
(A) Car driving simulation environment. (B) Control room for subject monitoring.

2 Materials

14 young and healthy subjects participated in the car driving simulation study, for which a laboratory with a real car, a large projection wall and a control room next to it was conceived as shown in Figure 1. For the experiment, the subjects had to arrive at the lab before 1:00 AM after a normal day of activity and a minimum of 16 h of continuous wakefulness. The experiment consisted of 7 driving sessions of 40 min, each followed by the responding of a questionnaire to assess sleepiness with a duration of 15 min and a short pause of 5 min before the next driving session began. By 8:00 AM the experiment should have ended. The road chosen for driving was a two-lane street with little curves and a non-varying landscape. The environment was intentionally designed to be monotonous to reduce vigilance, increase sleepiness and stimulate MSE. The manual annotation of MSE and its duration was carried out by two independent experts using three video streams acquired from the driving scene and subject [3]. No ethical approval was needed for this study.

A total of 15 different signals were recorded during the experiment including driving performance and biosignals such as pupil size based on an eye-tracking-system, electroencephalograms (EEG), electrooculograms (EOG), electromyograms (EMG) and the ECG. The latter was recorded at a sampling rate of 256 Hz using Einthoven lead II which is characterized by a large monophasic QRS complex and positive concordant P and T waves.

3 Methods

3.1 Signal preprocessing

For the purpose of reducing the impact of noise and other artifacts that can corrupt the morphological features, a prefiltering step is necessary. A phase free Butterworth high pass filter of order 6 with a cutoff frequency at 0.5 Hz was used to remove baseline wander. High frequency, muscle noise and power line hum were canceled using an equivalent low pass Butterworth filter with the cutoff frequency of 40 Hz [4].

3.2 ECG wave detection

The algorithm beginns with the detection of the QRS complexes. The method uses the stationary wavelet transform (SWT) to potentiate the spectral components of the signal located below 50 Hz what coincides with the spectral components of the QRS complex. An adaptive threshold is then applied and signal portions above threshold are labeled as QRS complexes. The T wave detection is the second step. Here, a PQRS cancellation is first carried out and an SWT is performed on the resulting signal. Again, signal portions located after the QRS complex that are above threshold are detected as the T wave. Having the QRS complex and the T wave, the ST segment can also be automatically annotated. Finally, the P wave is found in a similar manner as the T wave, but a cancellation of the QRST segment is performed before a new SWT of the resulting signal is computed.

3.3 Feature extraction

From an ECG signal a large variety of features can be obtained. Two main categories are distinguished, rhythmical and morphological. The rhythmnical features reflect the heart rate varibility (HRV) and are closely linked to the autonomous regulation of the heart. On the other side, the morphological features of the ECG waves capture the depolarization repolarization process in the heart and reflect the cardiac electrophysiology. In this work, we extracted features from both categories.

A segment of the ECG signal before and after the MSE was extracted from the ECG. Two type of analyses were carried out. In the first one, the length of the segment was chosen to be 120 s. In the second approach, the chosen segment was 30 s long. The change in temporal resolution was intended to investigate if there is a tendency to short-term or to long-term effects around the MSE.

Since no MSE were present in any of the subjects during the first 20 min of the very first driving session, we used that interval as reference. We utilized segments of the same length as the ones being analyzed to calculate the ECG features used as reference. We assume that the feature values obtained from those first 20 min are comparable to ECG descriptors during full vigilance. Finally, if two or more MSE were present within the same analysis interval, they were all removed from the study.

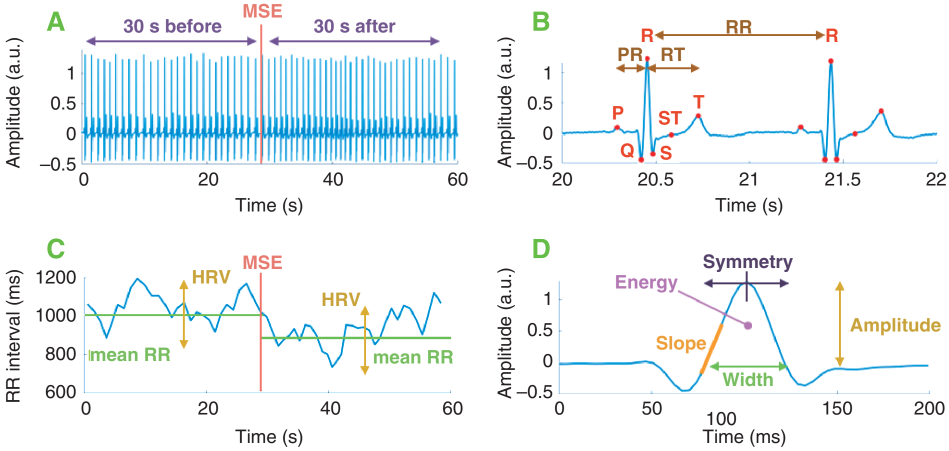

Figure 2: Signal processing work flow for feature extraction.
(A) Manually annotated MSE and its analysis interval of 30 s. (B) Automatic detection of ECG waves and wave intervals. (C) Extracted RR time series and its rhythmical properties. (D) Segmented QRS complex and its morphological features.

3.3.1 Rhythmical features

The series of RR intervals obtained from the ECG is used for the development of rhythmical descriptors. The feature extraction from this time series is primarily based on the analysis of heart rate varibility (HRV) [5]. Figures 2B and 2C display the RR time series and the meaning of HRV.

From the time domain, standard descriptors such as the mean RR, SDNN, rMSSD, PNN50 together with other geometrical and non-linear parameters were calculated.

For the frequency domain, a special consideration was taken for the RR time series because they were extracted from an ECG segment of the length 30 s or 120 s. In this case, the Welch's method cannot be successfully applied. For this reason, a periodic extension of the RR time series to a length of 5 min was performed followed by an interpolation to equally spaced RR intervals with a sampling rate of 4 Hz. The power spectral density (PSD) of the resulting series is then computed using the Welch method with a Hann window of 256 sample points, an overlap of 50% and a zero padding to 1024 sample points. From the PSD, standard features such as LF, HF, and LF/HF ratio were calculated.

The time-frequency domain was also used to generate features. For this purpose, the wavelet packet analysis (WPA) was carried out with the Daubechies Symlet 12, which delivers a good compromise between time and frequency resolution and its almost symmetrical shape reduces distortions in the transformed signal. For the WPA, an interpolation to a sampling rate of 2.4 Hz was chosen. This allows a frequency resolution of 0.0375 Hz and a time resolution of 13.33 s at decomposition level 5. From this transformed signal, similar features as the ones obtained from the time and frequency domain HRV analysis were also computed here.

A total of 242 features were obtained from the rhythmical properties of the ECG.

3.3.2 Morphological features

For the extraction of morphological features, every ECG wave is segmented in the signal. So for example, the QRS complex is extracted by placing an interval of 100 ms before and after the R peak. Analogously, the P wave, the ST segment and the T wave are also segmented considering their respective durations. Typically used wave descriptors such as amplitude, width, symmetry, curvature, peakness, slope, center of mass and energy were computed from all EGG waves. Time distances between the waves such as the PR or RT intervals and their dispersion (standard deviation of the intervals) were also calculated [2]. The corrected RT interval according to Bazett was also used as feature. Figures 2B and 2D briefly show how the PR and RT intervals together with the other morphological features are obtained.

In order to achieve morphological features that were comparable among different subjects and take into account the variability of the wave morphology within the same subject, we carried out a normalization of the morphological features. For this purpose, an ECG template was created from the beats of highest signal quality in the reference phase of the signal. Every morphological feature obtained from any part of the signal was subtracted from the corresponding feature value of the template.

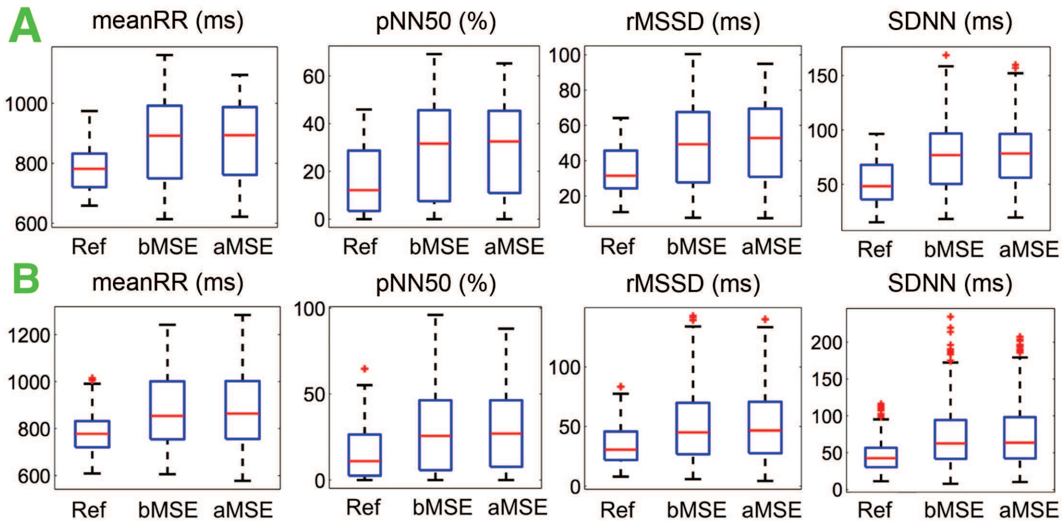

Figure 3: Results of the statistical analysis of rhythmical descriptors. (A) Analysis interval of 120 s. (B) Analysis interval of 30 s.

Then, the mean and standard deviation features computed from the beats used to create the template were used for normalization.

A total of 104 features were obtained from the morphological properties of the ECG.

3.4 Statistical analysis

For the purpose of comparing features coming from the reference interval, and the segments before and after the MSE, a Wilcoxon signed-rank test was performed. The statistical significance was assumed for an error probability (p-value) of $p < 0.05$.

A summary of the signal processing work flow developed for this work can be seen in Figure 2.

4 Results

We present a summary of the features that turned out to be most significant (lowest p value) for this study.

4.1 Rhythmical features

From the statistical analysis of the rhythmical descriptors, we observed that non of them had a significant difference in its median value before and after the MSE. However, when the features from the reference signal were compared to values when an MSE occurred, significant variations were present. In general, the mean heart rate decreased, while the HRV increased. For example, in the analysis of segments of 120 s, the parameter mean RR went from 788 ms (76 bpm) in the reference interval to approximately 880 ms (68 bpm) when MSE were present. A similar behavior was observed for other HRV parameters like rMSSD and pNN50 and for the signal length 30 s. Figure 3 summarizes the most significant results for the rhythmical features in the form of box plots.

4.2 Morphological features

We observed also that non of the morphological features had a significant difference before and after the MSE. As a matter of fact, the comparison between feature values from the reference signal and the MSE showed that the most significant morphological descriptors were also related to rhythmical properties. Among those descriptors, we observed an increase of the median values of the PR and RT corrected intervals and their dispersion. Figure 4 summarizes the most significant results for the morphological features.

5 Discussion

The statistical analysis showed that no feature had a significant change before and after an MSE. This demonstrates that, at least for this study, the ECG alone is not sufficient for the detection (or prediction) of MSE. This seems to

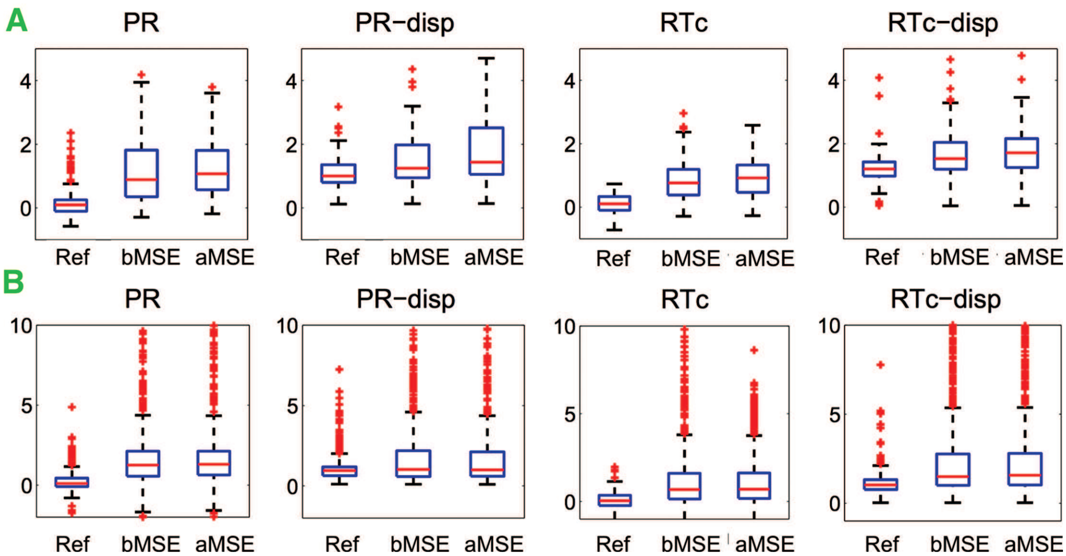

Figure 4: Results of the statistical analysis of morphological descriptors. (A) Analysis interval of 120 s. (B) Analysis interval of 30 s.

be conform with other studies that demonstrate that MSE are primary observable in the EEG [6]. However, when compared to the reference baseline values from the beginning of the experiment, we did observe that the heart rate goes down, while HRV and PR and RT segments between and their dispersion increase in the presence of MSE. This could be explained by a stronger parasympathetic activity on the cardiovascular regulation what is in accordance with what is known of HRV during no rapid eye movement stages of sleep [7].

6 Conclusion and outlook

The ECG alone is not sufficient for the detection of MSE, since no changes are observed in the short intervals before and after it. However, when compared to the reference baseline values, the ECG features do change significantly in the presence of MSE. This allows the possibility of using ECG descriptors for the quantification of sleepiness and monitoring of vigilance. For this purpose, a direct regression of ECG features to relate them to the level of drowsiness should be carried out. This would also facilitate the risk assessment of an MSE occurring.

Author's Statement

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