Original Research

Investigation of Sleep Deprivation Effect on Driver's Electromyography Signal Features in a Driving Simulator

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Abstract

Background and Objective: Sleep deprivation is an important cause of driver drowsiness. Surface electromyography (sEMG) of the upper arm and the shoulder is an important physiological signal affected by the driver drowsiness. The objective of this paper is to derive the pattern of sleep-deprived drivers' sEMG.

Materials and Methods: The tests were conducted on 7 men with no sleep disorder aged between 25 and 50 years in a driving simulator. Each subject participated in the tests once without sleep deprivation and another time with two hours of sleep in the 24-hour period before the tests. The sEMG signal from the upper arm and shoulder muscles were measured for the mid deltoid, clavicular portion of the pectoralis major, and triceps and biceps long heads. Four features including power spectral kurtosis (SK), mean frequency, absolute amplitude, and root mean square (RMS) were extracted.

Results: The k-nearest neighbors (k-NN) algorithm classifier detected drowsiness with 90% accuracy, 82% precision, 77% sensitivity, and 94% specificity. Driver's sleep deprivation can be detected through sEMG signal with 85% accuracy, 80% precision, 70% sensitivity, and 88% specificity.

Conclusion: The sEMG signal amplitude and the frequency content of the sleep-deprived subjects were higher than those of the normal subjects by 37% and 15%, respectively. For the sleep-deprived subjects, muscle contraction did not change much in transition between the last two levels of drowsiness, while the normal subjects experienced 27% drop in this transition. At the last level of drowsiness, the sleep-deprived subjects experienced mental drowsiness without significant change in the muscle contraction level.

Keywords: Sleep deprivation; Automobile driving; Surface electromyography

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Introduction

Driver drowsiness results in fatal road accidents every year. About 21% of fatal driving crashes between 2009 and 2013 in the United States of America (USA) were caused by falling asleep while driving (1). Researchers have employed several methods for detecting drowsiness of drivers. These methods are divided into three broad categories of vehicle dynamics, facial expressions, and physiological signals. Among these methods, physiological signals have a better accuracy and reliability for detecting drowsiness (2).

During driver's transition from being awake to falling asleep, several physiological features related to muscle movements change. Drivers initially resist to the sleep, so they experience muscle contraction first. Then, they yield to drowsiness and experience muscle relaxations. Electromyography (EMG) is the most accurate method to detect movements of muscles (3). Surface EMG (sEMG) measures muscle electrical activities via surface electrodes placed on the driver's arm skin. Electrical voltage is generated by each muscle contraction depolarization along its membrane. The changes in the electrical potential of the muscle membrane produced by the propagation of the action potential can be measured with electrodes (4).

Wireless EMG devices have the potential to be used in real-time driver drowsiness detection sys-

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tems. A wired EMG device impairs and interferes with the task of driving. In a study by Fu and Wang, a non-contact data acquisition system was used to collect the EMG data from the driver. It used complex computations with high processing power (5). In another study, wireless stainless-steel EMG sensors called Myo™ were used to evaluate muscle activities (6). Myo™ does not interfere with the driving task, but suffers from low signal-to-noise ratio. In addition, it cannot be placed exactly on the designated target muscle and may be displaced from the initial location while driving. We used regular wired EMG signals in this paper.

Sleep deprivation affects drivers' EMG features. The effect of sleep deprivation on the driving performance is comparable to that of sleep disorders such as narcolepsy. Sleep deprivation affects alertness, attention, and both rule-based and skill-based cognitive functions. Driver's ability to respond to a disturbance is reduced as a result of sleep deprivation (7). This paper provides a powerful tool for drowsiness researchers to detect normal drivers' sleep deprivation using low-cost wireless EMG systems. The main contributions of this paper are as follows:

- This paper shows how sleep deprivation affects EMG features such as power spectral kurtosis (SK), mean frequency, shape factor, absolute amplitude, geometric mean, and root mean square (RMS).
- EMG features can detect drowsiness with 90% accuracy.
- The elapsed time is not a reliable criterion for driver's estimation of drowsiness level caused by sleep deprivation; thus, time is replaced with the observer rating of drowsiness (ORD) in this paper.

Next, the experimental procedure including the driving simulator, test participants, and the EMG signal acquisition apparatus are explained. Then, the signal processing method used in this research is presented. Finally, the EMG features and their classification are described.

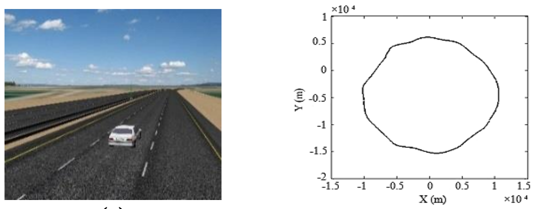
Materials and Methods

Tests were conducted in a driving simulator and signals related to the vehicle dynamics, facial expressions, and the EMG of the upper arm and the shoulder were recorded.

Driving simulator: The Nasir Semi 003™ driving simulator was used to conduct drowsiness tests as shown in Figure 1. The dynamic model of the virtual car has 14 degrees of freedom (DF) solved in real time. The lateral force of the road is applied to the steering wheel by a DC motor. The subject interacts with pedals and a shift stick. The virtual vehicle kinematic and kinetic data are recorded with the sampling rate of 30 Hz.

Figure 1. Nasir Semi 003™ driving simulator

The participants drove on a monotonous 67-km-long closed-loop three-lane highway. Figure 2(a) shows the highway scene from a third-person point of view. Figure 2(b) shows the top view of the quasi-circular highway. The radius of curvature was as large as 10 km to prevent sudden wakening up of the driver. The subjects were asked to drive as fast as 80 km/h to 100 km/h within the middle lane. If the drowsy driver applied no steering wheel torque, the car would depart from the lane.



(a) (b)

Figure 2. (a) Driving scene from a third-person point of view, (b) top view of the 67-km-long closed-loop driving path

Participants: The sufficient number of experimental sessions can be approximated with the assumption of a normal distribution. We used the Wald method (8) for binormal distribution with the 95% confidence results and the error band of 11%. This method requires 84 experimental sessions. It is equivalent to seven subjects participating in four sessions of the drowsiness tests. The subjects were men and aged between 25 and 50 years with the average age of 34.5 years.

The lifestyle and sleep data of the subjects were recorded. The following information was extracted from the questionnaire: age, general health, food, lifestyle, weight, body mass index (BMI), regular caffeine intake, and driving records. Prior sleep data in the week before the test were obtained from the sleep log including bedtime, wake-up time, and sleep duration for each night in the week leading to the test. Table 1 shows the demographic characteristics of the subjects.

Table 1. Demographic characteristics of the subjects

Subject number	Age (year)	Height (m)	Weight (kg)	BMI (kg/m^2)
1	25	1.73	83	27.73
2	25	1.89	100	27.99
3	30	1.76	75	24.48
4	50	1.68	89	31.53
5	40	1.78	88	27.77
6	37	1.78	69	21.77
7	26	1.72	55	18.59

BMI: Body mass index

Medical records of the subjects were also checked. They had a normal dominant shoulder function and no one had any sleep disorder, muscular disorder, history of shoulder pathology, and addiction to drugs, alcoholic drinks, and cigarettes.

The test procedure was observed by all subjects as it had been explained to them before the tests. The subjects had been allowed to watch TV or do any chore that did not require intensive physical activity during the past 24 hours before the test. The subjects were forbidden from drinking tea, coffee, or any other caffeinated beverages 6 hours prior to and during the test. The sleep deprivation tests were conducted by allowing the subjects to sleep for only two hours at the night prior to the test. For normal subjects, a similar experimental design was carried out, but with a regular full-night sleep. The beginning time of the tests was 1.5 to 3 hours after the subject's wake-up for normal subjects. The procedures were conducted in accordance with the Declaration of Helsinki.

The Maintenance of Wakefulness Test (MWT) was used to screen the subjects. A couple of days before the driving test, each of the seven subjects took an MWT. According to the American Academy of Sleep Medicine (AASM), MWT measures the ability to stay awake for a defined period of time (9). The subjects were asked to try to stay awake as long as possible during each test session. The trials were terminated after 40 minutes if no sleep had occurred, or after unequivocal sleep onset defined as 3 continuous epochs of stage 1 sleep or one epoch of any other stage of sleep had occurred (9). After the MWT, subjects with unusual behaviors were identified and excluded from the tests.

Signal acquisition: The sEMG signals from the upper arm and shoulder muscles were recorded. Electrodes had a 32 × 41 mm rectangular shape with the Ag/AgCl core material. They were placed in a bipolar formation at both muscle ends. Before the test, the designated muscles were rubbed with isopropyl alcohol. The reference ground electrode was installed on the subject's left hand wrist. The sEMG signal was recorded with eWave 32D from ScienceBeam™ at the sampling rate of 1 kHz. Superficial muscles having an important role in the task of driving were selected to locate the electrodes. These muscles are mid deltoid muscle, the clavicular portion of the pectoralis major muscle, and the triceps and biceps long heads (10-13). In Figure 3, the electrodes on the subjects' skin are shown.

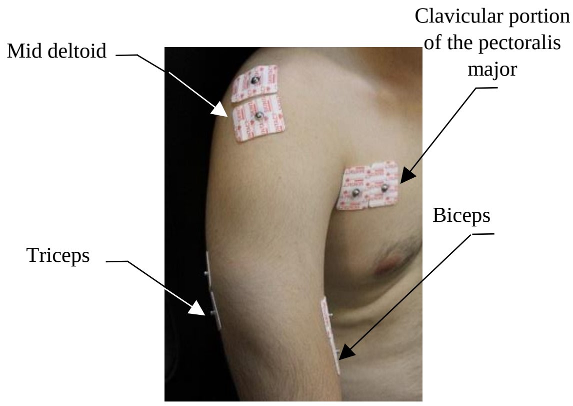


Figure 3. The surface electromyography (sEMG) electrode placement on the shoulder and the upper arm

The driver drowsiness level can be evaluated by non-physiological methods (14-16). Time is not a good criterion for analyzing driver drowsiness because of the non-stationary nature of drowsiness, especially during driving. For example, the driver may feel drowsy after a few minutes since the test begins but may return back to wakefulness after a lane departure. The ORD is a non-physiological method quantifying the level of driver drowsiness based on the judgments of human observers (16). Three dedicated and expert observers rated the drowsiness levels of the subjects over the course of driving. The criteria for scoring the drowsiness level included the facial and behavioral signs and the driving pattern. The scores were ranged between 1 and 5, 1 being the state of not drowsy and 5 indicating the state of extreme drowsiness. The sEMG features were analyzed for each level of the ORD rather than analyzing based on the elapsed time. At the first level of the ORD (not drowsy) and at the second (slightly drowsy), the driver is in the wakeful state and shows little fatigue sings. At the third level of the ORD (moderately drowsy), the driver begins to exhibit fatigue signs and struggles to fight against drowsiness. At the fourth level of the ORD (very drowsy), microsleeps (MSs) begin and the driver has a limited cognition about the driving environment. Finally, at the fifth level of the ORD (extremely drowsy), the driver makes little effort to stay awake.

Feature extraction: Time-domain and frequency-domain features of the EMG signal are affected by fatigue and drowsiness. 46 features were evaluated out of which 5 features were more sensitive to drowsiness. The frequency-related features including power SK and mean frequency and three magnitude-related features including absolute amplitude, geometric mean, and RMS were extracted.

Power spectral kurtosis (power SK)*:* This feature is a measure of power spectral probability distribution tailedness.

Mean frequency*:* Mean frequency is the total sum of the power spectrum of the signal product of the magnitude of frequency divided to the net sum of powers. The mean frequency shows how the frequencies shift as drowsiness increases.

Absolute amplitude*:* The absolute amplitude of the EMG signal is the average sum of the absolute magnitudes of signal. The amplitude of EMG signal shows the muscle contraction level.

Root mean square (RMS)*:* The RMS is a measure of the signal strength.

Results

The sEMG signals of the upper arm and the shoulder muscles were recorded for seven healthy subjects. One set of tests was conducted for subjects with normal sleep schedule and another set for the sleep-deprived subjects. Features most sensitive to the drowsiness levels are of prime interest to be used in the classification. We selected five features including power SK, mean frequency, absolute amplitude, geometric mean, and RMS. These features are more distinct in the moderate drowsiness state where the subjects struggle to fight against drowsiness.

Drowsiness level estimation: Sleep deprivation fastens the pace of the ORD increasing from 1 to 5. The percentage of time taken at each ORD level is an important feature in differentiating between normal and deprived subjects. Figure 4 and 5 show the percentage of ORD levels for normal and sleep-deprived subjects, respectively.

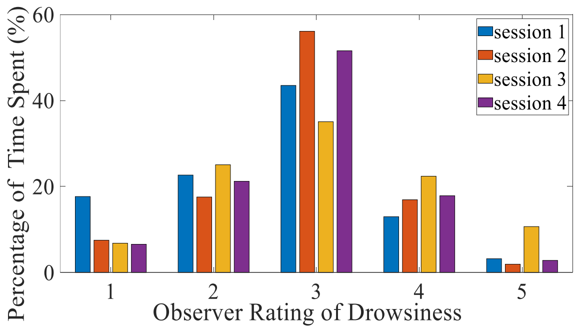


Figure 4. The percentage of the time spent at each level of the observer rating of drowsiness (ORD) for normal subjects

Normal subjects spent more driving time in the moderate drowsiness state compared with the time spent in the other four states of drowsiness within the 80-minute tests. Between 39%-50% of the session time was spent in the moderate drowsiness state (ORD = 3). Session 3 was the most perilous session as the percentage of time spent at this session for the very drowsy (ORD = 4) and the extremely drowsy (ORD = 5) states was more than that at other sessions.

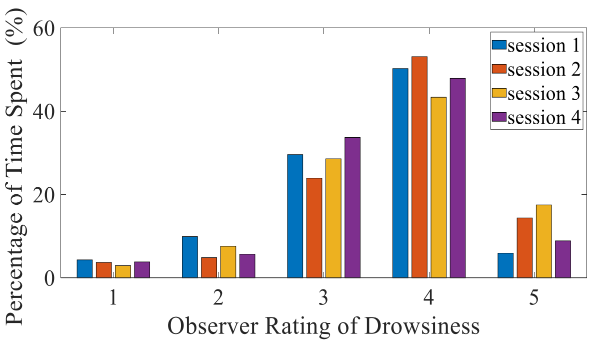


Figure 5. The percentage of the time spent at each level of the observer rating of drowsiness (ORD) for sleep-deprived subjects

The sleep-deprived subjects spent more time in the very drowsy (ORD = 4) state compared with other states. The deprived subjects spent between 42%-52% of their driving time in the very drowsy (ORD = 4) state. Similarly, they spent between 5-18 percent of their driving time in the extremely drowsy (ORD = 5) state, which is about twice of the time spent at this state by the normal subjects.

sEMG signal frequency and amplitude features: In transition from wakefulness to moderate drowsiness to extreme drowsiness, sEMG frequency and magnitude features change for both normal and sleep-deprived subjects with different trends. The magnitude of muscle fiber activation is specified by the neural drive. In transition from wakefulness to moderate drowsiness, the central nervous system (CNS) reduces the neural drive to the muscles and decreases the produced force (17, 18). In the moderate drowsiness level (ORD = 3), the driver attempts to compensate for the effect of reduction of the muscle performance and applies further force. When the MSs begin (ORD = 4), the neural drive to muscles is reduced further and the driver almost gives up to reverse muscle relaxation. In the extreme drowsiness (ORD = 5), the sEMG signals reach the lowest value.

The results indicated that the sEMG features for the sleep-deprived subjects did not change much from ORD = 1 to ORD = 5 compared with the normal subjects.

The power spectral density (PSD) of normal and sleep-deprived subjects shows noticeable differences in the frequencies of less than 100 Hz. Figures 6 and 7 show the PSD of the sEMG in the bandwidth of 10 Hz to 160 Hz, and ORD ranged between 1 to 5 in the normal and sleep-deprived subjects, respectively. The frequency was divided into periods of 10 Hz, the median of these periods across all frequencies were taken, which is shown in the figures 6 and 7.

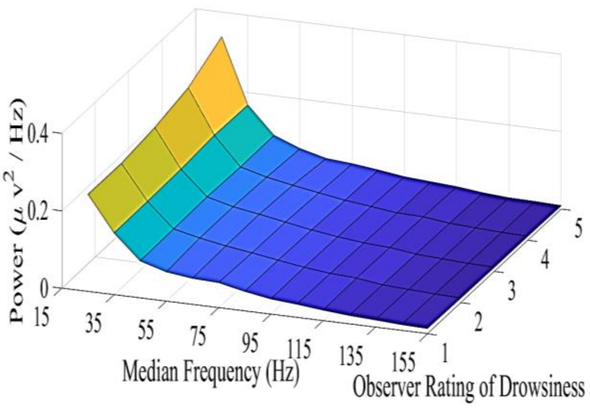


Figure 6. The power spectral density (PSD) of surface electromyography (sEMG) of normal subjects

As shown in the figures 6 and 7, the frequency content of greater than 100 Hz had a little power magnitude. The dominant spectral frequencies were between 10 Hz and 20 Hz.

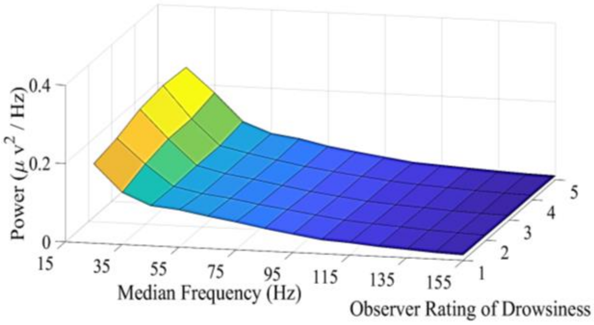


Figure 7. The power spectral density (PSD) of surface electromyography (sEMG) of sleep-deprived subjects

In the normal subjects, the dominant spectral frequencies power was about 3-10 percent more than sleep-deprived subjects in the different ORD levels, as shown in figure 8. The differences between normal and sleep -deprived subjects in the moderate drowsiness (ORD = 3) was minimum and increased in the next ORD levels.

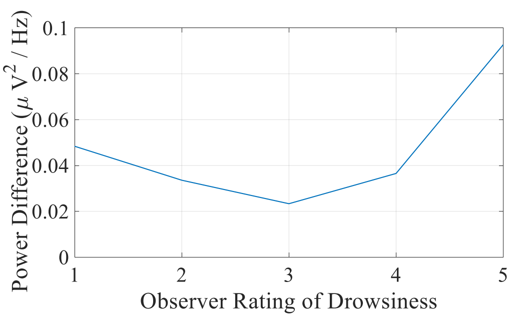


Figure 8. The power spectral density (PSD) difference between normal and sleep-deprived subjects in the 10 Hz and 20 Hz bandwidth

In the range of 30 Hz to 100 Hz, the power of sEMG changes with respect to ORD. Figure 9 shows the PSD for a) wakefulness, b) moderate drowsiness, and c) extreme drowsiness in both normal and sleep-deprived subjects.

Next, the results for two frequency-based features and four magnitude-based features are presented.

A. Power SK

Figure 10 shows the mean of power SK for the normal and sleep-deprived subjects. The kurtosis was larger by 5%-30% for the normal subjects compared with the sleep-deprived subjects. The reason is that the normal subjects had a richer low-frequency content of 10-20 Hz resulting in a more tailed distribution. This is consistent with figure 8 that shows that the PSD for the normal subjects is higher than that for the sleep-deprived subjects at all levels of drowsiness within the bandwidth of 10-20 Hz. This is also consistent with Figure 9 as the sleep-deprived subjects have a more concentration of the PSD in the mid frequencies of 35 Hz to 95 Hz resulting in a smaller kurtosis.

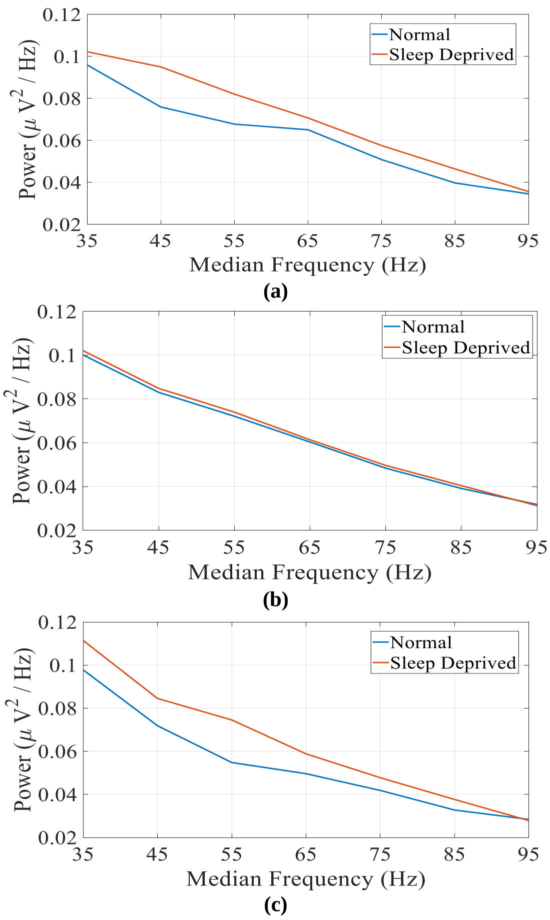


Figure 9. The power spectral density (PSD) between 30 Hz and 100 Hz for normal and sleep-deprived subjects in a) wakefulness, b) moderate drowsiness, and c) extreme drowsiness

Figure 11 shows the normalized power SK of the a) normal and b) sleep-deprived subjects at the sEMG bandwidth of 10-350 Hz.

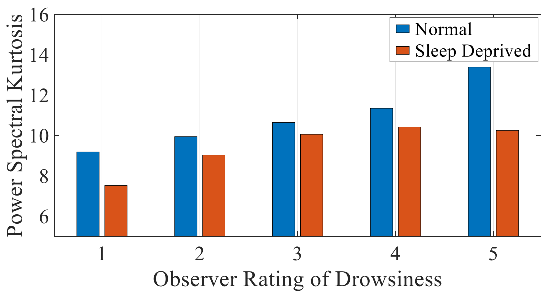


Figure 10. Surface electromyography (sEMG) power spectral kurtosis (SK) of normal and deprived subjects before normalization of the signal

In Figure 11(b), the power SK feature for each subject is normalized by dividing by his maximum Euclidean length. This normalization makes it possible to compare the normal and sleep-deprived feature trends more easily. The normalization also removes interindividual differences and makes the trends of drowsiness levels more meaningful. Normalization is only used to better represent the data in the boxplots. No normaliztion was done in the classification of the data.

For the normal subjects, the normalized power SK had an ascending pattern. For the deprived subjects, the power SK had a maximum at the moderately drowsy state (ORD = 3). We concluded that the sleep-deprived subjects did not have a very distinct pattern of PSD kurtosis at different levels of drowsiness; a wakeful sleep-deprived driver (ORD = 1) exhibited a PSD kurtosis almost at the same level as the PSD kurtosis at the extremely drowsy state (ORD = 5).

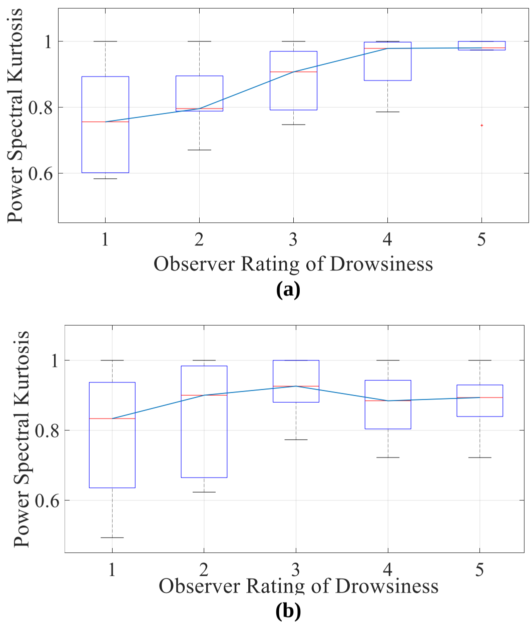


Figure 11. The boxplots of the normalized power spectral kurtosis (SK) for a) normal and b) sleep-deprived subjects

B. Mean frequency

As the level of drowsiness increased, the high-frequency contents of the sEMG signal were reduced resulting in lowering of the mean frequency. Figure 12 shows the mean frequency decreases from 56.4 Hz to 47.3 Hz monotonically for the normal subjects and from 61.6 Hz to 53.0 Hz for the sleep-deprived subjects.

The mean frequency of the sleep-deprived subjects was higher than that of the normal subjects. The normal subjects were richer in the low-frequency bandwidth of 10-20 Hz. On the other hand, the sleep-deprived subjects were richer in the bandwidth of 30-100 Hz. Thus, the mean frequency feature of the sleep-deprived subjects was higher than that of the normal subjects at all levels of drowsiness. At the moderate level of drowsiness (ORD = 3), the sEMG signal of the normal subjects increased to resist against falling asleep, making it closer to the mean frequency of the sleep-deprived subjects. At wakefulness (ORD = 1), the mean frequency of the sleep-deprived subjects was higher by 5.1 Hz compared with the normal subjects. This difference narrowed to 2.0 Hz at the moderate level of drowsiness (ORD = 3), and increased again to 5.6 Hz at the extreme level of drowsiness (ORD = 5).

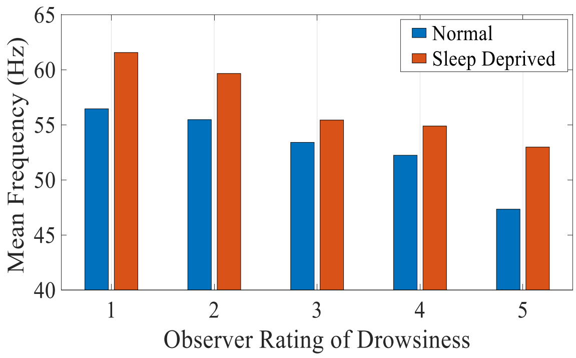


Figure 12. Surface electromyography (sEMG) mean frequency of normal and deprived subjects before normalization of the signal

Figure 13 shows the normalized mean frequency of the normal and sleep-deprived subjects at the sEMG bandwidth of 10-350 Hz. Sleep deprivation causes muscle contraction even during extreme drowsiness.

The normalized mean frequency trend of the sleep-deprived subject declined from wakefulness (ORD = 1) to extreme drowsiness (ORD = 5) by only 5.2%. In contrast, this decline for the normal subjects was 13.2%. In particular, there was a sudden fall of 8.2% from the very drowsiness level (ORD = 4) to the extreme drowsiness level (ORD = 5) for the normal subjects.

C. Absolute amplitude

The mean absolute amplitude of the sEMG decreases at higher levels of drowsiness. For the normal subjects, the muscles contraction level increased from 4.9 mV during the wakefulness (ORD = 1) to 5.5 mV during the moderate level of drowsiness (ORD = 3) as shown in figure 14.

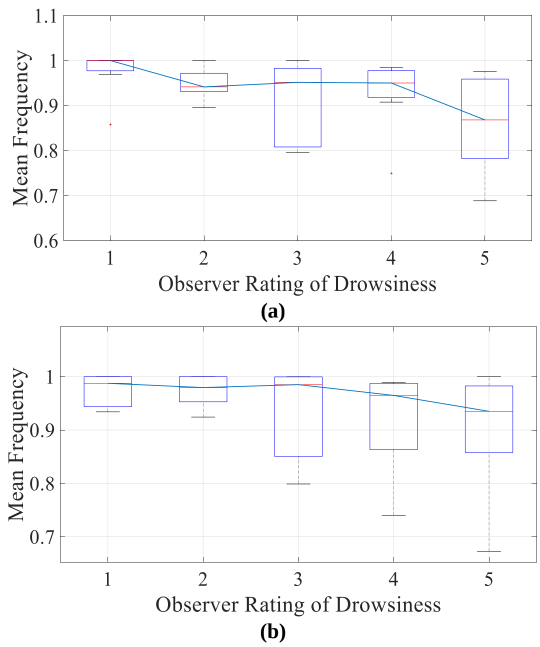


Figure 13. Normalized boxplot of the mean frequency for a) normal and b) sleep-deprived subjects

This was equivalent to only 12.1% rise. Then, it underwent a steep drop of 52.8% to 2.6 mV at the extreme level of drowsiness (ORD = 5). The sleep-deprived subjects had a different pattern. The absolute amplitude of the sEMG remained rather constant at 6.0 mV from wakefulness (ORD = 1) to moderate drowsiness (ORD = 3). Then, it underwent a mild drop of 17.0% to 5.0 mV at the very drowsy level (ORD = 4) and remained constant at extreme drowsiness (ORD = 5).

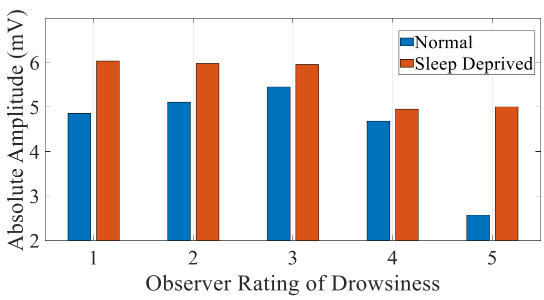
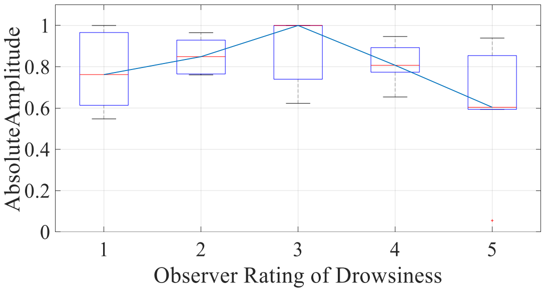


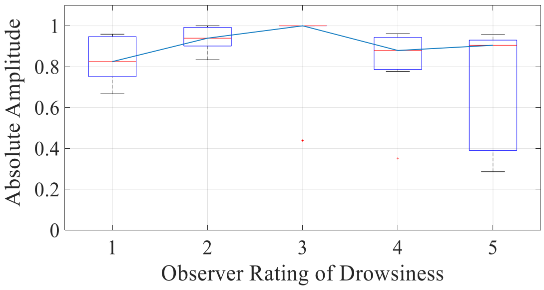
Figure 14. Surface electromyography (sEMG) mean absolute amplitude of normal and deprived subjects before normalization of the signal

The absolute amplitude of the sEMG signal for the deprived subjects was more than that of the normal subjects. Sleep deprivation results in the driver fatigue and more muscle contraction. On average, the difference of the absolute amplitude between the sleep-deprived subjects and the normal subjects was 0.7 mV from the ORD = 1 to ORD = 4. At extreme drowsiness (ORD = 5), this difference was 2.4 mV, which was significantly higher than that in the previous ORDs.

Figure 15 shows the normalized sEMG absolute amplitude of a) normal and b) sleep-deprived subjects. The median of the absolute amplitude reached to a maximum at the moderate drowsiness (ORD = 3) and declined at the ensuing ORD levels. The median of the absolute amplitude of the normal subjects at ORD = 5 was 39.6% lower than that at ORD = 3. This percentage for the sleep-deprived subjects was 10%.



(a)



(b)

Figure 15. Normalized boxplot of the mean absolute amplitude for a) normal and b) sleep-deprived subjects

D. RMS

The RMS for the sleep-deprived subjects remained almost constant at 13.4 mV for all ORD levels as shown in figure 16. For the normal subjects, it increased by 6.7% from 9.7 mV during the wakefulness (ORD = 1) to 10.4 mV during the moderate level of drowsiness (ORD = 3). It then experienced a drop of about 25.7% at the extreme drowsiness level.

The RMS of the sleep-deprived subjects had a higher value than that of the normal subjects. In the moderate drowsiness (ORD = 3), this difference between the sleep-deprived and normal subjects was 28.8% and reached 71.9% in the extreme drowsiness (ORD = 5). The sleep-deprived subjects experienced higher levels of muscle contraction resulting in higher RMS values.

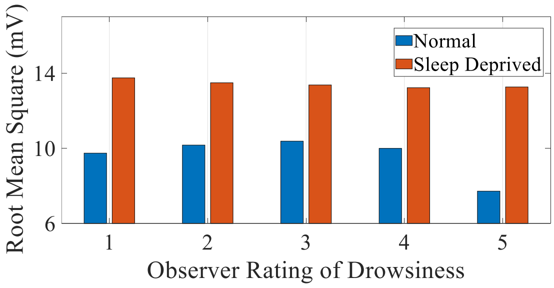
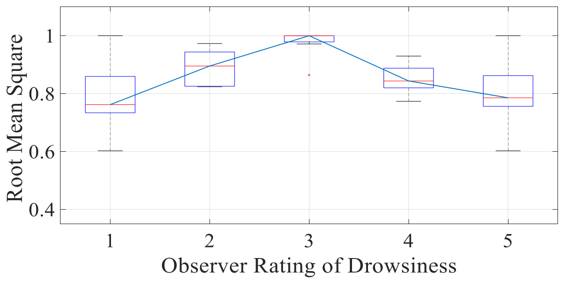
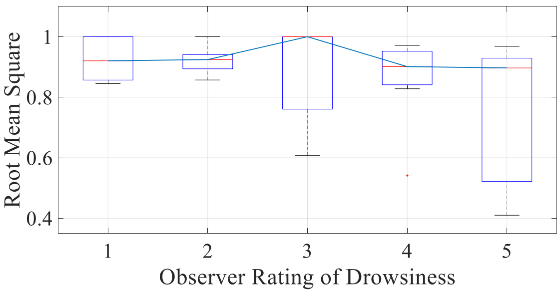


Figure 16. The Surface electromyography (sEMG) root mean square (RMS) of the normal and sleep-deprived subjects before normalization of the signal

The normalized RMS patterns in both the normal and the sleep-deprived subjects showed a maximum at the moderate drowsiness (ORD = 3) as shown in Figure 17(a and b). The differences between the maximum and the minimum normalized RMS for the normal and the sleep-deprived subjects were 23.8% and 11.3%, respectively. In other words, the normalized RMS of the sleep-deprived subjects was rather constant and independent of the ORD levels. Sleep deprivation was the dominant factor in the median RMS of the sEMG signals.



(a)



(b)

Figure 17. Normalized boxplot of root mean square (RMS) for a) normal and b) sleep-deprived subjects

Classification: The drowsiness levels were classified based on the sEMG features. The moderate drowsiness level (ORD = 3) plays an important role in the driver sleep drowsiness detection as s/he applies countermeasures to drowsiness (19). After this level, MSs begin. So, detection of this level of drowsiness can result in an early prevention of MSs and reduction of driving accident risks. In the classification conducted in this paper, the first three levels of the ORD, i.e., 1, 2, and 3, are categorized as wakeful, and the last two levels of the ORD, i.e., 4 and 5, are categorized as drowsy. Driving is safe in the first three levels and unsafe in the last two levels. 70% of the data were randomly used for training, 15% for validation, and 15% for testing.

Learning-based methods are suitable for processing biological signals even at the presence of noisy and missing data. Computational feasibility is an important advantage of these methods. The main idea of these classifiers is to map the feature space to a higher order for better data separation.

The k-nearest neighbors (k-NN) algorithm is a learning-based classifier. In this method, neighbors are selected from the nearest set of objects having the minimum difference in the intended property. This classifier achieved the best performance of 90% accuracy, 82% precision, 77% sensitivity, and 94% specificity.

The classification results also showed that the driver sleep deprivation can be detected through sEMG signal with a high accuracy of 85%, 80% precision, 70% sensitivity, and 88% specificity.

Discussion

This study investigated the sEMG features of the normal and sleep-deprived subjects during transition from wakefulness to extreme drowsiness for seven healthy male subjects. The lifestyle and the sleep data were recorded from all subjects and completed through a questionnaire. They had a normal dominant shoulder function and no one had any sleep disorder, muscular disorder, and history of shoulder pathology. Prior sleep data in the week before the test was obtained from the sleep log. The results are valid for healthy male subjects with no addiction to drugs, alcoholic drinks, and cigarettes.

The tests were conducted in a driving simulator on a monotonous 67-km-long closed-loop three-lane highway. Drowsiness was evaluated with the non-intrusive ORD method. It is advantageous to the self-reported measurements such as the Karolinska Sleepiness Scale (KSS) and the Stanford Sleepiness Scale (SSS), as it does not cause awakening and sudden reduction of the drowsiness level of the subject.

Most drivers underestimate the deteriorating effect of the sleep deprivation on driving and the risk of falling asleep at the wheel. The sleep-deprived drivers may spend most of their driving time experiencing MSs and sudden shifts between states of slight drowsiness (ORD = 2) and extreme drowsiness (ORD = 5). There is a misconception among many drivers that if they do not suffer from sleep disorders, it would be safe to drive even with sleep deprivation.

Conclusion

The sEMG signal amplitude and the frequency content of the sleep-deprived subjects were higher than those of the normal subjects.

The sEMG amplitude-related features of the sleep-deprived subjects changed less during wakefulness to moderate drowsiness transition compared with those of the normal subjects.

For the sleep-deprived subjects, muscle contraction did not change much between the drowsiness levels of 4 and 5, while the drop between these two levels was very significant (27%) for the normal subjects. In other words, at the last stage of drowsiness, the sleep-deprived subjects experienced mental drowsiness as would be observed by the electroencephalography (EEG) signals, while the muscle contraction level stayed almost at the same level as that in the very drowsy level of 4.

The sEMG signal amplitude and the frequency content of the sleep-deprived subjects were higher than those of the normal subjects by 36% and 15%, respectively. The sEMG amplitude of the sleep-deprived subjects changed less during wakefulness to moderate drowsiness transition compared with that of the normal subjects.

In the future, one can compare the sEMG signals of patients with sleep disorder with those of the healthy subjects under sleep deprivation.

Conflict of Interests

Authors have no conflict of interests.

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