Coherence Validation of Alternative Sleep EEG Electrode Placements Using Wavelet Transform

Shih-Chung Chen¹,* Aaron Raymond See¹ Chun-Ju Hou¹ Yeou-Jiunn Chen¹ Chih-Kuo Liang² Po-Yang Hou¹ Wen-Kuei Lin¹

¹Department of Electrical Engineering, Southern Taiwan University of Science and Technology, Tainan 710, Taiwan, ROC
²Department of Electrical Engineering, National Taitung College, Taitung 950, Taiwan, ROC

Abstract

Recent studies on automated sleep stage classification have started to adopt alternative sleep encephalography (EEG) electrode placements on the forehead as opposed to the traditional C3-C4 placement. The current study determines the validity of adopting the prefrontal EEG electrode placement. First, EEG signals were decomposed into four harmonic bands using the discrete wavelet transform and their power spectrum densities were extracted for comparison. The correlation coefficients of both signals were calculated and jackknifed to determine an unbiased statistical value. The signal and its power spectrum displayed moderate to very strong values of the correlation coefficient, respectively, with minute standard errors and biases. A strong coherence is exhibited between both electrode placements as viewed from the power spectra of different sleep stages. The magnitude-squared coherence values indicate that the reduction in the coefficient values for the beta band was due to a low correlation in a certain frequency band. Manual sleep stage classification was also conducted by a sleep technician and sleep stage classification software, with consistent results obtained. Sleep stage scoring using both methods indicated substantial agreement for the standard and alternative electrode placements. In conclusion, this work shows a strong coherence for the prefrontal and standard electrode placements and corroborates the hypothesis of using the alternative placements for performing quick, convenient, and efficient measurement and analysis of EEG signals.

Keywords: Sleep encephalography (EEG), Prefrontal EEG, Discrete wavelet transform, Correlation coefficient, Jackknife analysis, Magnitude-squared coherence

1. Introduction

Research on sleep has increased in the past decade mainly due to the rising number of people suffering from sleep disorders [1,2]. A traditional analytic method for studying sleep is polysomnography (PSG), which uses multiple electrodes to acquire physiological signals. However, this is not only uncomfortable for the patients and expensive for frequent diagnosis, but also time-consuming for sleep technicians. Several automated sleep stage classification methods have thus been developed [3-7]. Various methods have been proposed to minimize the number of physiological electrodes. Single- or dual-channel electroenoculography (EOG) [8,9] and single-channel electrocardiography (ECG) [10] have been used, but single- or dual-channel electroencephalography (EEG) is the most promising method for minimal-electrode sleep analysis [3,4,6,11]. For traditional EEG recordings for sleep assessment, based on the Rechtschaffen and Kales (R&K) rule, electrodes are placed on the C3-A2 and C4-A1 regions. However, it is rather challenging for a person to properly place multiple physiological electrodes, or even a single EEG electrode, in these areas to measure their sleep quality [12]. Consequently, automated sleep stage classification systems that use single-channel EEG have been proposed. Several studies have used prefrontal EEG to determine sleep deprivation [13,14], and others have used the prefrontal region for sleep stage classification [15]. An alternate EEG placement to the traditional C3-A2 to Fpz-Cz placement was proposed [15]. It was shown that the two electrode placements have significant agreement. However, there were instances in which a deeper sleep stage was recorded using the alternative placement.

The study on the alternative electrode placement aims to support the advancement of the studies on automated sleep staging. Numerous studies on the utilization of feature extraction techniques and classification techniques have been conducted [5,6,11] but few have considered alternative electrode placements [15]. A recurrent neural classifier and energy
features were used for automatic sleep stage classification. The traditional C3-A2 electrode placement was considered as an independent variable for sleep stage classification [11]. In another study, it was determined that sleep deprivation has a greater relative increase in the concentration of delta and theta activities in the frontal EEG derivations compared to their parietal and occipital counterparts [16].

Furthermore, the electrode placement at the prefrontal region, as stated in the International 10-20 system, provides a preview of the cortical areas essential for executive control and attention control. Prefrontal EEG measurements can also provide features necessary to determine borderline sleepiness [17-19]. The main advantage of using prefrontal EEG is that it provides convenience, which is important for home use, as it allows the user to more easily mount and clean a device compared to its scalp electrode counterpart.

An in-depth analysis of EEG signals requires separating the signal into several harmonic parameters. EEG signals are non-stationary and thus should not be processed using traditional spectrum analysis methods. Traditional methods provide a representation of EEG signal frequency but cannot accurately replicate its timing. Wavelet analysis is considered a satisfactory method for analyzing EEG signals, as it provides localization in both time and frequency [5]. Furthermore, the wavelet transform can be used to extract trends, discontinuities, and repeated patterns. The discrete wavelet transform (DWT) has been proven to be a robust tool for detecting transitions from an alert to a drowsy state [20-22].

The present study investigates whether Fp1-A2 and Fp2-A1 electrode placements are analogous to C3-A2 and C4-A1 placements using DWT decomposition and statistical analysis without compromising the traditional R&K rule.

2. Materials and methods

The comparative analysis of the alternative EEG electrode placement proposed in this paper includes the following processes: data acquisition, signal preprocessing, feature extraction, sleep stage scoring, and statistical analyses. First, PSG recordings were obtained from experiments conducted in a sleep laboratory. Second, EEG signals from the C3-A2/Fp1-A2 and C4-A1/Fp2-A1 regions were extracted for analysis. Third, these signals were preprocessed using a low-pass filter and a linear detrend function. Fourth, feature extraction of the various harmonic bands was carried out using the DWT. Fifth, the power spectrum of each harmonic band was extracted. Sixth, a correlation coefficient was calculated and jackknifed to compare the signals, as harmonic bands individually or as a whole signal in each sleep stage. Seventh, the magnitude-squared spectral coherence was calculated to study the relationship of the harmonic frequencies at different electrode placements. Finally, the physiological signals were used to manually and automatically score and determine the sleep stages. The EEG signals from the prefrontal (Fp1-Fp2) and the traditional fronto-central (C3-C4) regions were separately used with EOG and electromyography (EMG) to perform the sleep stage classification. Results of sleep stage classification were statistically compared.

2.1 Participants

The sleep recordings used in this study were obtained from a total of 15 healthy/normal volunteers recruited to undergo sleep assessment to determine the utility and efficacy of the alternate electrode placements. All subjects had normal hearing, normal or corrected-to-normal vision, and no history of substance abuse, major medical psychiatric illness, or developmental or neurological disorder. The subjects were all male with an average age of 22.54 ± 1.78 years old.

2.2 Experimental procedures

PSG sleep recordings were performed during the participants’ 2-h naps under standard recording conditions in a sleep laboratory. Data were recorded using a commercial device (Somite™ PSG, Compumedics Limited, Abbotsford, VIC, Australia). The following physiological signals were continuously recorded: EEG (C3-A2, C4-A2, Fp1-A2, and Fp2-A1), horizontal EOG, chin EMG, heart rate, respiration (nasal/mouth flow), and oxygen saturation (obtained using an oximeter). The sampling rate for the EEG acquisition was 200 Hz.

Data from multiple physiological signals were acquired to perform automated sleep staging using the ProFusion™ PSG software bundled with the PSG device. Although complete PSG was measured, the current study is limited to the statistical analysis of the alternative electrode placement from the traditional C3-A2/C4-A1 channels to the Fp1-A2/Fp2-A1 channels, respectively. EEG data were stored for later analysis and then exported to a .txt file for further processing. The resulting sleep stages were also stored in a separate file to analyze changes in different epochs. Subsequently, each epoch is analyzed for various sleep stages: waking (W), non-rapid eye movement sleep 1 (N1), non-rapid eye movement sleep 2 (N2), non-rapid eye movement sleep 3 (N3), and rapid eye movement sleep (REM). The EEG data were divided into 30-s samples, giving a total of 4478 epochs. The datasets have a total of 947 waking epochs, 575 N1 epochs, 1823 N2 epochs, 908 N3 epochs, and 225 REM epochs. In the study a total of 18 2-h datasets that corresponds to 4320 epochs were used. The excess of 158 epochs on the total number of epochs mentioned above were excluded from the analysis as these were pre- or post-measurement signals. The participants gave informed consent and the sleep study was approved by the Institutional Review Board (IRB) of National Cheng Kung University Hospital.

2.3 Signal preprocessing

The EEG signals were first preprocessed using a 5th order Butterworth low-pass filter with a cutoff frequency set at 60 Hz. Then, the signals were further processed using a linear detrend function to remove trends from the multivariate time signal before they were subdivided into 30-s epochs. Subsequently, the signals were normalized before feature extraction. The data were normalized using the statistical profile mean and standard deviation to calculate the normalized vector. The normalization process is calculated as the quotient of the difference of the signal and mean and the standard deviation.
2.4 Feature extraction

DWT multi-resolution analysis was used to decompose the EEG signal. A Daubechies wavelet of order 4 (db4) was selected for this task. In [23], the authors found that a db4 wavelet was suitable for investigating epileptic EEG signals. Lower-order wavelets are coarse whereas higher-order wavelets contain substantial oscillations that make spike detection more challenging [23]. Using the continuous wavelet transform, it was found that delta rhythm in deeper sleep stages has significant variations. In addition, the average power spectral density spectrum was able to highlight K-complex waves and a gradual increase in power from deeper sleep stages due to the delta wave increase [24]. However, the drawback of using a continuous wavelet transform is the redundancy in the signal’s representation. Consequently, in this study, the EEG signals were decomposed using the DWT into a series of dyadic frequency sub-bands composed of the detail coefficients D1-D4 and one final approximation coefficient A4 using the db4 mother wavelet. In this study, detail coefficients D2-D4 and the final approximation coefficient A4 exhibited an approximation of the harmonic bands beta, alpha, theta, and delta, respectively. The EEG wavelet decomposition is shown in Table 1. In addition to the harmonic bands, their power spectra were also extracted for analysis. The Welch power spectrum density with a 50% overlap was used to provide smooth power spectra.

<table>
<thead>
<tr>
<th>Decomposition level</th>
<th>Decomposition label</th>
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<th>Bandwidth (Hz)</th>
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<td>Gamma</td>
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<td>30</td>
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<tr>
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<td>Beta</td>
<td>15-30</td>
<td>15</td>
</tr>
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<td>7.5</td>
</tr>
<tr>
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<td>D4</td>
<td>Theta</td>
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<td>3.75</td>
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<tr>
<td>5</td>
<td>A4</td>
<td>Delta</td>
<td>0-3.75</td>
<td>3.75</td>
</tr>
</tbody>
</table>

2.5 Correlation coefficient and jackknife analysis

Jackknife and correlation coefficient analyses were used to statistically evaluate the different harmonic bands and their corresponding power spectra. The correlation coefficient is the most common relational statistic used to evaluate the strength of two variables, which in this study are prefrontal EEG placement and central EEG electrode placement. The correlation coefficients were calculated on a second-by-second basis and were recalculated using 30-s intervals representing an epoch.

The Pearson correlation coefficient assesses the interdependence of two variables and represents how closely they co-vary in a range of -1 to +1, where -1 and +1 indicate perfect negative correlation and perfect positive correlation, respectively. The statistical significance was set at 0.05 for 95% confidence intervals.

Jackknife analysis is commonly used as a data partitioning method similar to cross-validation, but its results are more similar to those of the bootstrap method. Jackknife analysis is often used in statistical inference to determine the bias and standard error estimates of a statistic. It produces consistent estimates [25].

The jackknife method can be explained as follows: First, leave one observation out from \( x_i \) observations for a sample to create a jackknife sample as follows:

\[
x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n
\]

Second, the \( i \)-th jackknife replicate \((T_{i,0})\) is determined by calculating the statistic of the remaining sample points:

\[
T_{i,0} = \{(x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n)\}
\]

Third, the previous two steps are repeated until all \( n \) observations of the jackknife replicates are determined. Fourth, the estimate \( \hat{\text{Bias}}_{\text{Jack}}(T) \) of the bias of \( T \) is obtained as:

\[
\hat{\text{Bias}}_{\text{Jack}}(T) = (n - 1) (\overline{T}_n - T)
\]

Where

\[
\overline{T}_n = \frac{1}{n} \sum_{i=1}^{n} T_{i,0}
\]

Fifth, the standard error \( \hat{\text{SE}}_{\text{Jack}}(T) \) using the jackknife method is then calculated as:

\[
\hat{\text{SE}}_{\text{Jack}}(T) = \left[ \frac{n - 1}{n} \sum_{i=1}^{n} (T_{i,0} - \overline{T}_n)^2 \right]^{1/2}
\]

2.6 Magnitude-squared coherence

Another method for determining the relationship between two signals is magnitude-squared coherence (MSC). Spectral coherence is widely used in EEG-related studies, which include those on the reduced fronto-cortical brain connectivity during NREM sleep in Asperger syndrome (AS) to distinguish children with autism [26,27]. MSC makes use of the averaged Welch power spectrum density to determine the correspondence of the x and y signals at each frequency. A Hamming window is used. In this study, the MSC of the harmonic bands was calculated to examine the coherence \( C_{xf}(f) \) of the power spectra at different electrode placements, is defined as:

\[
C_{xf}(f) = \frac{|P_{xf}(f)|^2}{P_{xx}(f)P_{yy}(f)}
\]

where \( P_{xf} \) is the cross-spectral density between x and y, and \( P_{xx} \) and \( P_{yy} \) the autospectral density of x and y respectively. The magnitude of the spectral density is denoted as \( |P| \).

2.7 Sleep stage classification comparison

After evaluating the correlation of the alternative electrodes, a comparison of the stages obtained using the traditional C3-C4 electrode placement and the alternative electrode placement was made to further demonstrate the validity of the proposed method. A sleep technician was instructed to manually determine the sleep stages using EEG measurement from the traditional electrode placement with the help of EOG and EMG measurements. Afterwards, EEG signals from the alternative EEG electrode placement were used with the same EOG and EMG readings. Results of the manual sleep stage classifications were then compared with the automated sleep stages produced by the ProFusion™ PSG software.
3. Results and discussion

A total of 37.32 hours of sleep data were recorded and analyzed from the 15 volunteers using the proposed alternative electrode placement. The electrodes were separately compared between the left and right hemispheres. The left hemisphere consisted of C3-A2 and Fp1-A2, and the right hemisphere consisted of C4-A1 and Fp2-A1. The EEG signals from 2 pairs of electrodes in each hemisphere were compared on a second-by-second and epoch-by-epoch basis, with each epoch being 30 s. EEG signals are first decomposed using multi-resolution analysis into different harmonic parameters using wavelet decomposition. A sample of the decomposed signal from the Fp1 channel of dataset 2 is shown in Fig. 1. Figure 2 shows a comparative diagram of the normalized power spectrum in each harmonic band. It can reasonably be deduced that there is coherence between the alternative placement and traditional placement.

Additionally, the validity of the alternative electrode placement was investigated by calculating the correlation coefficient of the decomposed signals and their power spectra. Results of the mean jackknifed correlation coefficient of the EEG signals from the left hemisphere electrode placement, C3-A2 and Fp1-A2, and their corresponding power spectra are shown in Table 2. Those from the right hemisphere electrode placement, C4-A1 and Fp2-A1, and their corresponding power spectra are shown in Table 3. The decomposed signals only have a moderate correlation, with coefficients of between 0.48 and 0.65. However, the power spectra have a very strong correlation for each of the harmonic bands, with values ranging from 0.90 to 0.97. It should be noted that the correlation coefficient of the signal’s power spectra is significantly higher than that of the decomposed raw EEG signal. The standard error and bias both had minimal standard error and bias. The difference for both the time and frequency domains is due to the difference in concentration of the different frequency bands in the prefrontal region. This is consistent with previous studies on sleep deprivation. One study showed a greater relative increase in the power density of delta and theta activities in the frontal EEG in comparison to electrode placements in the parietal and occipital counterparts [16]. The state of sleepiness resulting from total sleep deprivation was positively correlated with the theta band EEG power from the prefrontal area [13,14].

The epoch-by-epoch correlation coefficients in different sleep stages were compared. Sleep stages with identical sleep scores were further analyzed. Data were categorized into different sleep stages, namely waking, N1, N2, N3, and REM. The mean correlation coefficient of each harmonic band’s

![Figure 1. Second-by-second sample of a decomposed EEG signal for Subject 2. Normalized decomposed EEG signals of (a) beta, (b) alpha, (c) theta, and (d) delta waves.](image)

![Figure 2. Comparative diagram of EEG power spectrum density for Fp1-Fp2 electrode placement and its C3-C4 counterpart for (a) beta, (b) alpha, (c) theta, and (d) delta waves.](image)

![Table 2. Mean jackknifed correlation coefficients for C3-A2 and Fp1-A2. (a) EEG signals and (b) power spectrum.](table)

<table>
<thead>
<tr>
<th></th>
<th>Corrcoeff</th>
<th>SE</th>
<th>Bias</th>
<th>Corrcoeff</th>
<th>SE</th>
<th>Bias</th>
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<tr>
<td>Beta</td>
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<td>0.897</td>
<td>0.013</td>
<td>0.0013</td>
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<tr>
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<td>-0.0007</td>
<td>0.943</td>
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<tr>
<td>Theta</td>
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<td>0.965</td>
<td>0.008</td>
<td>0.0004</td>
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<tr>
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<td>0.963</td>
<td>0.008</td>
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<tr>
<td>Mean</td>
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<td>0.026</td>
<td>-0.0005</td>
<td>0.942</td>
<td>0.010</td>
<td>0.0007</td>
</tr>
</tbody>
</table>

*a* Correlation coefficient

![Table 3. Mean jackknifed correlation coefficients for C4-A1 and Fp2-A1. (a) EEG signals and (b) power spectrum.](table)

<table>
<thead>
<tr>
<th></th>
<th>Corrcoeff</th>
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<td>0.0210</td>
<td>0.955</td>
<td>0.008</td>
<td>0.0007</td>
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<tr>
<td>Theta</td>
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<td>0.967</td>
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<td>Delta</td>
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<td>0.0156</td>
<td>0.968</td>
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<tr>
<td>Mean</td>
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<td>0.005</td>
<td>0.0204</td>
<td>0.952</td>
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</tr>
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</table>

*a* Correlation coefficient

*b* Standard error
Coherence Validation of Alternative EEG Electrode Placements

power spectra in various sleep stages are shown in Fig. 3. The figure shows that the correlation coefficients of both C3-Fp1 and C4-Fp2 were generally relative except in some instances for both the beta and alpha waves. The C4-Fp2 alternative placement showed significantly higher correlation in all the harmonic bands for almost all sleep stages.

![Correlation Coefficient](image)

**Figure 3.** Correlation coefficient of power spectra for the different harmonic bands in various sleep stages.

The electrode placements at the prefrontal region showed a substantial correlation with the fronto-central electrode placement. In contrast to a previous study [15], wherein two independent observers were asked to rate the sleep stages and Cohen's kappa value was used for statistical analysis, the current study uses signal processing techniques to decompose the signal into its basic harmonic bands before comparing using the correlation coefficient. In theory, the decomposed signals obtained using wavelet transform retain both the time and frequency components, which are crucial for an accurate comparison. According to Fig. 2, there were instances wherein the signals of the alternative placements had some frequency shifts at higher frequency bands, such as the beta band. This phenomenon can be attributed to the characteristics of wavelet multi-resolution analysis, which has good time resolution but poor frequency resolution at high frequencies. However, it is notable that the lower-frequency signals were good approximations of those obtained using the original electrode placement, except for the difference in power amplitude. Figure 4 shows the curve of the correlation coefficient from 3600 sleep epochs. The percentage difference of the alpha and beta bands was calculated. From the diagram, the delta harmonic band has the highest correlation for both electrode placements. Alpha and theta harmonic bands have relative coherence while beta has a slightly lower correlation. The percentage difference between the alpha and beta bands in the C3-Fp1 placements has an average of 3.56% and a maximum of 41.11%. However, the percentage difference between the alpha and beta in the C4-Fp2 placements has an average of only 3.02% and a maximum of 21.88%. These values indicate that frequency shifts at higher frequency bands can cause a reduction in the correlation coefficient.

![Correlation Coefficient Curve](image)

**Figure 4.** Correlation coefficient curve of sleep epochs compared using the different harmonic bands based on (a) C3-Fp1 placements and (b) C4-Fp2 placements.

From Fig. 4, the delta band has the highest correlation while the beta band has a slightly lower correlation compared to those of the other three harmonic bands. It can be observed in Fig. 5 that certain frequency drops were manifested between the 25 Hz and 35 Hz frequencies. The coherence in the beta band was lower than those in the other frequency bands, as shown in Fig. 5. These lower-MSC regions contributed to the lower correlation between the two electrode placements.
Although this study is limited to 2-h sleep studies, it can
be noted from the R&K rule that one sleep cycle is estimated to
be 90 to 100 min, which is well within the scope of the 2-h
study stated in the experimental procedure [12].

To provide consistent estimates of the error and bias, the
correlation coefficients were jackknifed to determine their
standard error and bias. These values account for the use of
prefrontal EEG electrode placement for sleep EEG acquisition
and analysis, as done by previous researchers [5,6]. Relatively
high values for the coefficients convey that the power spectrum
signals of the different harmonic bands have a strong

correlation. The harmonic band’s power spectra were the
primary feature investigated in several sleep classification
systems [3,4,10,28] and in studies on sleepiness and sleep loss
[14,16]. The current study validates the use of prefrontal EEG
electrode placement. Epochs with the same sleep stage for both
electrode placements were analyzed. The average correlation
coefficients and standard deviations of the power spectra for
the C3-Fp1 alternative are 0.938 ± 0.025, 0.942 ± 0.016,
0.939 ± 0.028, 0.945 ± 0.0343, and 0.934 ± 0.068 for wakening,
NREM 1, NREM 2, NREM 3, and REM, respectively. Those
for the C4-Fp2 alternative are 0.932 ± 0.021, 0.944 ± 0.026,
0.941 ± 0.032, 0.949 ± 0.036, and 0.970 ± 0.031 for wakening,
N1, N2, N3, and REM, respectively.

A hypnogram obtained from one dataset with at least 2 h
of sleep from the manual sleep stage classification is shown in
Fig. 6. The manually scored sleep data were compared with the
results of the automated sleep stage classification. Agreement
between the standard and alternative electrode placements were
calculated using Cohen’s kappa. One set was found to have a
very low kappa with values calculated to be 0.275 and 0.288
for the sleep stage classification using the C3-C4 electrode
placement and the Fp1-Fp2 electrode placement, respectively.

Figure 5. MSC values of low-pass-filtered signal for (a) C3-Fp1 and (b)
C4-Fp2 placements.

There were instances wherein the sleep technician scored a
sleep stage but the automated system scored “waking”. This
was due to noisy signals; some of the electrodes could have
been pressed due to head movement or the impedance was
affected by external causes. Hence, the abovementioned low
kappa valued dataset were considered as outliers and excluded
in the mean calculation of the kappa. The recalculated kappa
values ranged from 0.470 (moderate agreement) to 0.949
(almost perfect agreement) for the C3-C4 electrode placements.
They ranged from 0.422 (moderate agreement) to 0.952 (almost
perfect agreement) for the Fp1-Fp2 electrode placements. The
definition or conditions for the kappa were derived from [28].

Mean kappa values for the datasets excluding the outlier was
0.771, which is considered to be substantial agreement.

Figure 6. Hypnogram of manual sleep stage classification using (a)
traditional electrode placement (C3-C4) and (b) alternative
electrode placement (Fp1-Fp2).

4. Conclusion

Discrete wavelet decomposition was used to study the
harmonic bands in EEG analysis. Results show a strong

correlation between both alternative electrode placements, with
the C4-Fp2 placements being stronger. From MSC analysis, the
reduction in the coefficient values for the beta band was due to
a low correlation in a certain frequency band. Sleep stage
scores obtained using both manual and automated scoring
showed a substantial agreement for the standard and alternative
electrode placements. This work showed strong coherence for
the prefrontal and standard electrode placements and
corrobates the hypothesis of using the alternative placement
for performing quick, convenient, and efficient measurement
and analysis of EEG signals. In the future, improvements on
the algorithms would be developed to improve the usability of
alternative electrode placements for sleep or brain computer
interface applications.

Acknowledgments

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