IMPROVEMENT OF EEG SIGNAL RECORDING WITH NON-CONTACT ELECTRODES IN AN HEADSET SYSTEM

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ABSTRACT

This paper presents methods in recording satisfactory EEG signals using non-contact capacitive EPIC electrodes in a headset system. The method involves incorporating only a single pair (two) of non-contact capacitive electrodes, positioned at targeted site of the scalp. The second important aspect is the consideration of the headset systems for maintaining stable position and contact at the interface between headset-based non-contact EPIC electrodes system and the targeted sites of scalp skin. The critical aspect is the optimization evaluation of contact pressure at the interface between headset-based non-contact EPIC electrode and scalp to minimising movement of the electrode with respect to the skin, and this will directly affect the optimal quality of the recording EEG signals. Thus, the classification performance of the recorded EEG signals can be optimised with maximum of subject comfort.

KEYWORDS

EEG recording method, Non-contact electrode, Headset system, Optimization, EEG classification.

1. INTRODUCTION

Although basics of the brain electrical scalp recordings of human have been the same since it was first performed by Hans Berger in 1929[1], the technological developments give the opportunity to build much more sophisticated acquisition systems regarding clinical needs and scientific research communities. The human brain generates cortical electrical signals called EEG signals which are roughly in very low amplitude range (typically 1-100 μV) and very low frequency behaviour (less than 100Hz) related to body functions, and acquired by electrodes non-invasively placed on the scalp of the head. This paper is about their recording.

The main problem in EEG recording is that these signals are generally obscured by transient signal noises and large-amplitude artefacts which can also produce power increases at specific frequencies and affect their classification accuracy of EEG signals, and then usability. In that sense, method to record good EEG signals should be considered.

This paper presents method for recording EEG signals using non-contact capacitive EPIC electrodes in a headset system. The method involves incorporating only three non-contact capacitive EPIC electrodes, positioned at targeted site of the scalp. The second important aspect is the consideration of the headset systems for maintaining stable position and contact at the interface between headset-based non-contact EPIC electrodes system and the targeted sites of scalp skin. The critical aspect is the optimization evaluation of contact pressure at the interface between headset-based non-contact EPIC electrode and scalp to minimising movement of the electrode with respect to the skin, and this will directly affect the optimal quality of the recording

EEG signals. Thus, the classification performance of the recorded EEG signals can be optimised with maximum of subject comfort.

We will thus record EEG simultaneously with non-contact EPIC electrode and wet contact electrodes.

2. METHODS

We used bipolar configuration for measuring the EEG signals. The set-up shown in figure 1 describes that the placement of the electrodes was in agreement with the bipolar configuration by placing three non-contact EPIC electrodes on the occipital region of the headset system at O1, T4 and T3, representing the sensing electrode (s), the reference electrode (r) and the ground electrode (g)

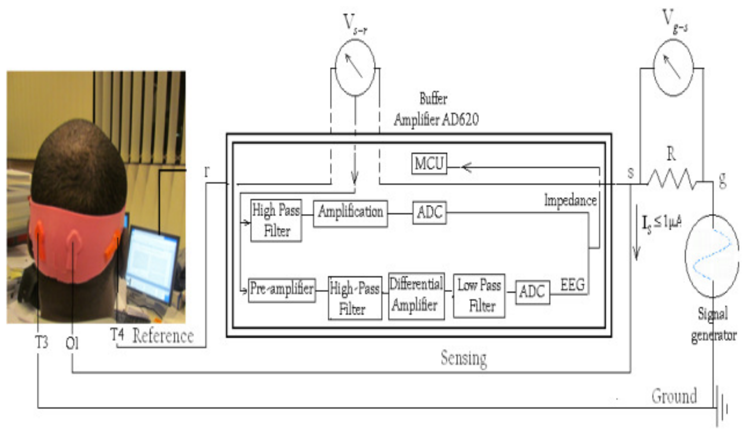

Figure 1: Block diagram for measuring skin-electrode impedance and EEG.

Each of these three non-contact EPIC electrodes was incorporated simultaneously with gold wet electrodes about 5 cm away from each other. The headset was fixed at optimal applied pressure to maintain a mechanical stability between the electrode and scalp skin.

2.1. Impedance Measurement

In order to obtain the impedance signal, a sinusoidal signal current is applied among electrodes g and s through a resistor in series *R,* then the current that crosses the electrode s, can be calculated by measuring the voltage drop V_{g-s} across resistor *R* for:

$$I_s = \frac{V_{g-s}}{R} \quad (1)$$

Voltage in points s and r generated by the measurement current I_s was buffered with the instrumentation amplifier AD620 (G=10, CMRR=100 dB), and was measured with an oscilloscope Instex GOS-622G (Input impedance: 1MΩ // 25 pF). The measured sinusoidal voltage signal is first high pass filtered so that DC component and the EEG from the skin-electrode interfacial contact are removed from the signal. Then, any voltage that appears among the electrodes s and r is due to the impedance Z_s that is the impedance of the union of the sensing electrode s with the skin. Consequently,

$$Z_s = \frac{V_{s-r}}{I_s} = R\frac{V_{s-r}}{V_{g-s}} \tag{2}$$

Finally signal is amplified and converted into digital form. A 16-bits differential analogue-to-digital converter (ADC) was used to acquire the amplified and filtered signal from electrode, with frequency of 256 samples per second. The skin-electrode contact impedance was therefore measured at 256 different frequencies range between 1 and $1000\,\mathrm{Hz}$ with a maximum of $1\mathrm{V_{pp}}$, where the injected current is proportional to the selected resistor at $100\,\mathrm{nA}$ to $1\,\mu\mathrm{A}$. The resistor $\mathrm{R} << 200\ \mathrm{M\Omega}$ was large enough to secure this constant current condition in the circuit. All measurements were taken without averaging and all data were recorded in the analyser and then downloaded to a host PC employing the software provided by the manufacturer.

2.2. EEG recording

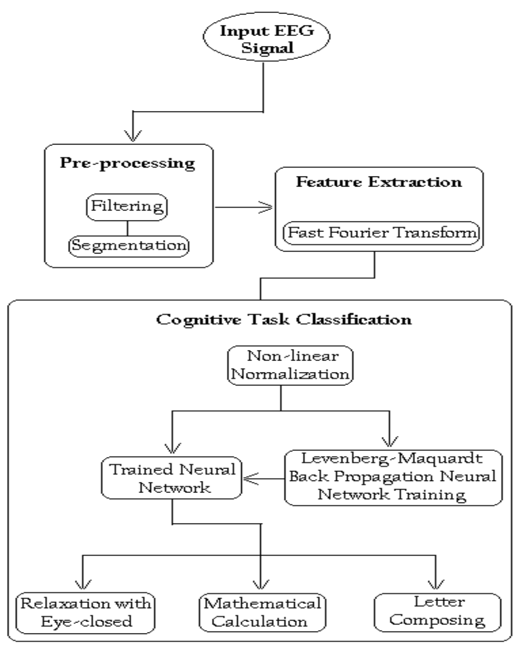

Figure 2. Overall flow of the data processing for classification.

EEG is detected from the measurement signal by first low-pass filtering the measurement signal (Figure 1), which removes the high frequency signals from the skin-electrode impedance contact[2,3]. Next the EEG signal is amplified and digitized. A 12-bits differential analogue-to-digital converter (ADC) was used to acquire the amplified and filtered signal from electrode, with sampling rate of 256 Hz. The sampled signals were then sent wirelessly to a computer for processing. The overall flow of the proposed processing is presented in Figure 2.

The processing steps include pre-processing and feature extraction[4]. Pre-processing including filtering, digitizing, artefact removing and DC level correction are to be applied on the EEG signals. Feature extraction part focus on extracting features accurately using FFT-PSD technique as described in the previous chapter. Following the parameterization, classification is performed using Feed Forward Back-Propagation Neural Network (BPNN) trained using Levenberg-Marquardt algorithm. All processing and analysis were performed in Matlab R2009b, using scripts for processing data[5].

3. EXPERIMENTAL RESULTS

All measurements were performed on eight (8) disabled subjects (6 males including 2 dark-skinned and 4 fair-skinned, and 2 females including 1 dark-skinned and 1 fair-skinned). All participants were volunteers and had a similar educational background, taking no medication, and reporting no medical treatments or health problems. The experiment was undertaken at the Centre for Health Technologies (CHT) at an ambient temperature of 23 ± 2 ◦C and a relative humidity between 50 and 55%, with the understanding and written consent of each participant, following the recommendations of the ethics committee of the University of Technology Sydney-Australia.

3.1. Impedance

The contact impedance to several frequencies was obtained varying the injected current to obtain a better noise-signal ratio. Before starting the measurements, we observed the warm-up time of 30 min after electrode placement, and then we performed a calibration to guarantee reliable and reproducible results. The test signal of the impedance spectroscopy was set to 1 V and the frequency range from 0.5 to 1000 Hz. Twenty four tests were performed on height different subjects in this study.

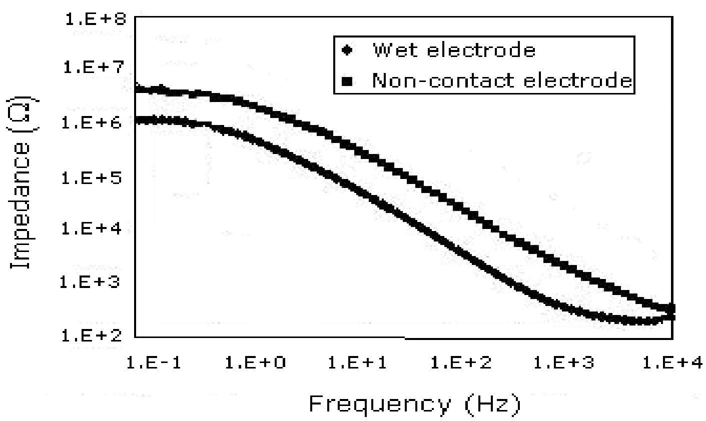

Figure 3. Impedance measurement at different frequencies, when comparing non-contact EPIC electrode simultaneously with gold-wet electrodes

Figure 3 shows the absolute values of impedance measurement results under different frequency conditions. When comparing the absolute impedances, the wet gel electrode has the lowest impedance. There is roughly one order of difference between the wet and dry electrodes. Figure 4 shows the fitting approach on a Cole-Cole plot using the Levenberg–Marquardt algorithm for electrode-scalp impedance spectral evaluation for the non-contact EPIC electrodes, dry electrode with bristles and gold wet electrodes, corresponding parameters are summarized in Table II. The measurements showed a more negative impedance phase for non-contact EPIC electrode, mean that the non-contact EPIC electrodes are more capacitive than bristle dry electrode and gold-wet electrodes for low frequencies.

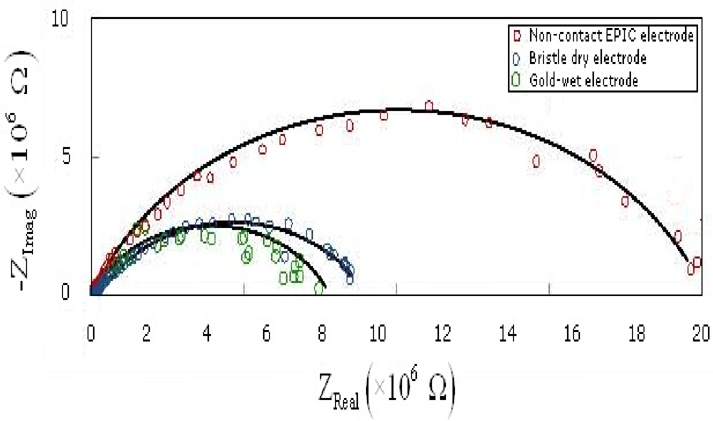

Figure 4. Cole-Cole plot and fitting of coating impedance.

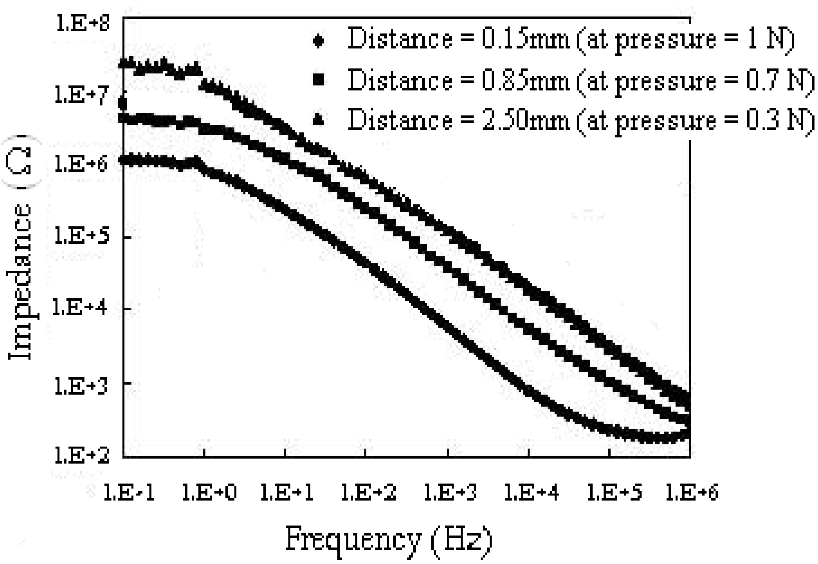

Figure 5. Impedance spectrum comparison between three different applied forces: 0.3N, 0.7N and 1N.

3.2. Impedance measurement at different applied forces

To characterize the performance of the sensor at various distances, three different applied force values (0.3N, 0.7N and 1N) are considered to squeeze and mechanically maintain the non-contact EPIC electrode on the scalp skin targeted sites, and then current was applied to the electrode pair to measure the impedance. The smallest distance is that created by just the solder-mask, which is estimated to be 0.15mm. The two larger distances are formed with spacers made of an acrylic plastic. Its dielectric constant of about 4 is roughly the same as that of human hair[6]. When comparing the absolute impedances (Figure 5), there is roughly one order of difference between the three applied forces. The normalized impedance results show that the non-contact electrode pressed at 1N outperforms others (0.3N and 0.7N), and even has the lower impedance in all range of frequency than when electrode is pressed at 0.3N or 0.7N.

3.3. Impedance Measurement for Long-term Monitoring

Figure 6 shows the averaged values of the long-term impedance variation (5 h) for five subjects. The long-term impedance variation of the conventional wet electrode with conduction gel is more obvious than that of our non-contact EPIC capacitive dry electrode. The impedance variation of our non-contact electrode was observed in the range from 4kΩ to 26kΩ, and is in the acceptable range for normal EEG measurement[7]. Furthermore, the non-contact dry electrode used can significantly provide better stability of the skin–electrode interface impedance because it does not need conduction gel, which is apt to drying.

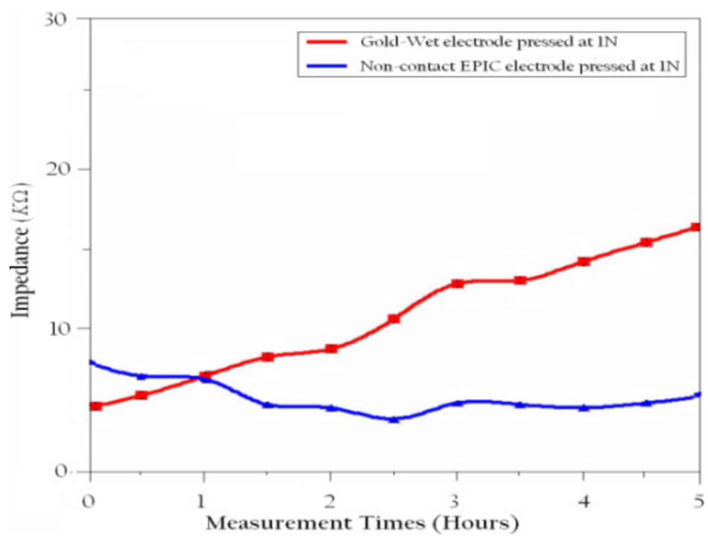

Figure 6. Comparing the impedance variation between the non-contact and wet electrodes for long-term measurement on the occipital site (O1).

3.4. Spectral Analysis

Figure 7 shows spectrograms of EEG data taken during a trial where a subject was asked to close their eyes from the segment spanning 5 to 20 seconds into the trial. The absence of alpha activity was confirmed by a non-contact control electrode placed on the forehead. The integrated sensor was able to resolve alpha waves through hair over the occipital region.

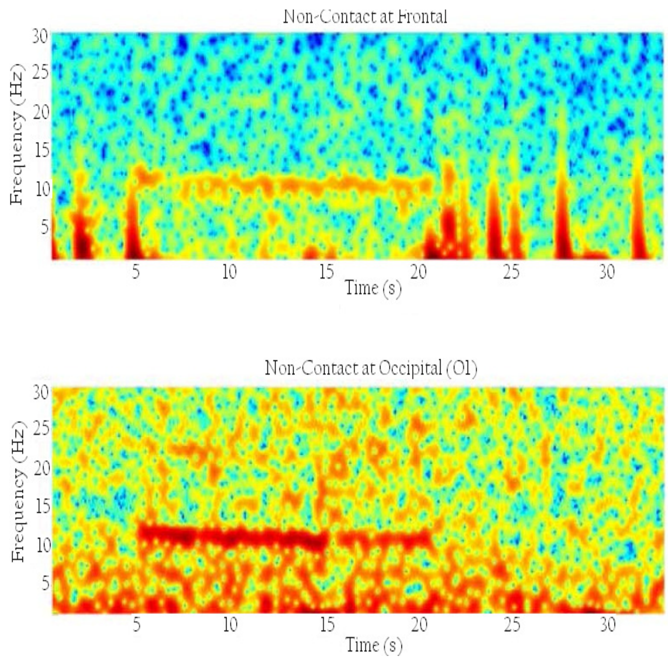

Figure 7. Spectrograms of EEG data when subject was asked to close their eyes from the segment spanning 5 to 20 seconds into the trial. The absence and the presence of alpha activity when non-contact electrodes are placed on the forehead and occipital.

3.5. Motion Sensitivity

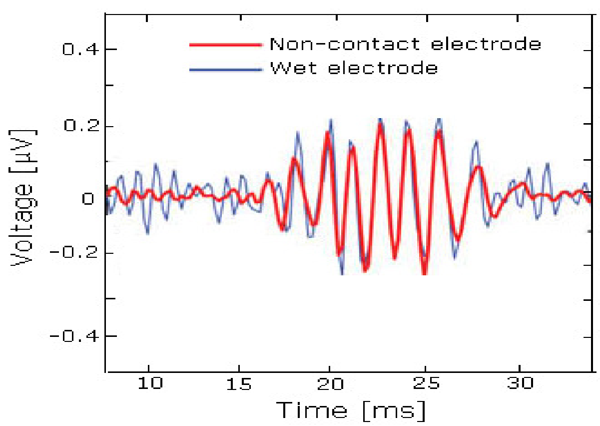

Figure 8: Comparison of noise between wet gold and non-contact electrodes across five subjects during fast motion.

In this experiment, EEG measurements were carried-out using the non-contact EPIC electrode simultaneously with wet electrode to investigate whether it is possible to perform unsupervised fast recordings with non-contact EPIC sensor.

To this end, we recorded ongoing EEG while the participant is at resting condition with eyes open for around 10s. While recording, high-frequency oscillation evoked by median nerve stimulation test was carried-out. This fast EEG activity is visibly in the 17.5–30 ms time interval with an amplitude of around 0.2 – 0.4 μV (Figure 8).

3.6. Noise calculation

To help facilitate objective comparisons, we have computed the level of noise when non-contact EPIC electrode is used in recording EEG signals. For this purpose, the time-domain EEG signal from G-electrode in simultaneous comparison with its counterparts recorded by our proposed dry non-contact EPIC electrode is shown in Figure 9. From first glance, the amplitude from the wet electrode almost perfectly matches that from the non-contact, verifying that it is indeed capable of acquiring EEG signals through hair.

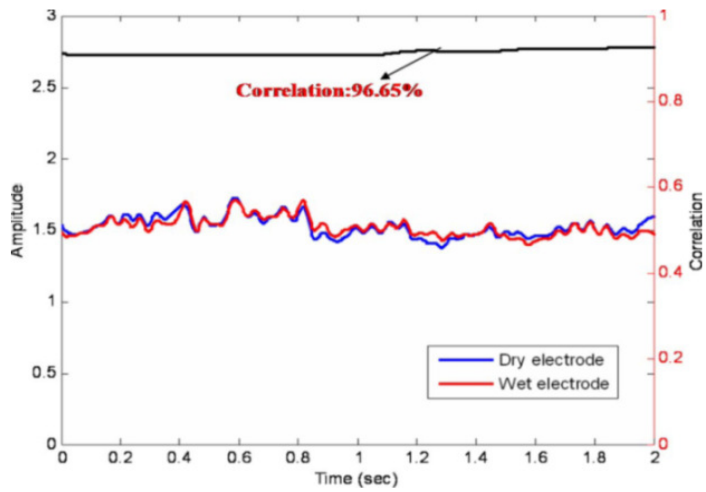

Figure 9: the time-domain EEG signal from gold wet electrodes in simultaneous comparison with dry non-contact EPIC electrode while subject is resting with eyes-closed for around 15s.

For quantitative analysis of the signal quality from the various electrode types, a few key parameters are desired. First, it is useful to obtain a metric that conveys how close the signal from non-contact electrodes matches the signal from a 'gold standard' wet electrode. Secondly, it is also useful to know the ratio, or SNR Specifically for this experiment, After the EEG signal quality has been verified by the user, the application can switch to canonical correlation analysis (CCA) mode, provided by each electrode showing the amount of useful cognitive EEG signal versus the background noise. Correlations between dry and wet difference latencies were obtained by calculating bivariate correlations (Pearson correlation), which were tested for significance by a one sample *t*-test against zero. The probability of getting a correlation as large as the resulting one by chance, if true correlation was zero, was evaluated against a significance level of 0.05. For confirmation, the same event was experimentally repeated also to the remaining four subjects. Their amplitude profiles, not included here, showed optimal match between both non-contact electrode and wet electrode in all tested subjects similar to figure 9.

Table 1. Signal correlation and computed SNR (in decibel) between no-contact and wet electrodes

Subject	Sensor Correlation	SNR (dB)	
	N-C vs Wet	N-C	Wet
1	0.85	-12.7	-11.4
2	0.96	-9.3	-8.5
3	0.93	-10.2	-7.8
4	0.91	-11.5	-7.1
5	0.88	-10.4	-9.5

A summary of the computed correlations can be found in Table I. Results shown that bivariate correlations could not show any significant differences in amplitude for both recording electrodes across subjects. Over half (three) the subjects had a correlation of greater than 0.9 (0.96, 0.93 and 0.91) and the remaining (two) subjects had correlation values of above 0.8, between non-contact and wet electrodes. Some minor differences in the oscillatory burst are likely to be due to differences in spatial locations and skin preparation of electrodes.

EEG data collected were also used to examine the peaks and troughs of a wave differ on an average from the mean voltage using the standard deviation. For analysing the statistical feature of a signal, the signal's mean has to be computed. It can also be claimed that the mean value is the average value of a signal. The signal mean value is determined by:

$$\mu = \frac{1}{N}\sum_{i=0}^{N-1} x_i \tag{3}$$

where μ represents the signal mean and the signal contained in x_0 through x_{N-1} and i denote an index that goes through these values. Using the equation **Error! Reference source not found.**, the standard deviation is computed as,

$$\sigma_{std} = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N-1}\left(x_i - \mu\right)^2} \tag{4}$$

which represents the noise and other inferences. The signal to noise (SNR) is thus calculated by dividing the mean by the standard deviation value.

$$SNR\left(dB\right) = 20\log_{10}\left(\mu/\sigma_{std}\right) \tag{5}$$

Computed values in Table 1 shown that the signal quality or instantaneous SNR using non-contact electrodes was less significant compared with the wet gold-electrodes between subjects. They are always well below 0 dB due to the small amplitude of the alpha EEG signal relative to the background EEG and noise.

The complete analysis could confirm that electrodes used were in good contact with reduced noisy. However, if the electrodes were in poor contact and noisy, causing the recording electrodes to drift synchronously, then the correlation value should increase towards one, irrespective of how well the individual sensors are performing.

3.7. Cognitive task classification

In this section, the results of classification experiment performed for recording cognitive task using non-contact and wet electrodes are presented. For data acquisition, subjects were requested to keep eyes open while seating in a sound-proof, dimly-lit, room and given a mental task for fifteen (15) seconds and each task was repeated five times per session. Since the duration of each test was 15 seconds, each subject took in total between 45 to 60 minutes to complete all 5 tests, the survey and the briefing. Following is the detail of the two (5) tasks performed by each participant [8] :

- Task 1 - *Relaxation*: With their eyes closed, subjects were instructed to relax as much as possible and think of nothing in particular, for five minutes, in the means to best achieve this purpose. This is considered to be the baseline session for alpha wave production, and other asymmetries.
- Task 2 - *Mental Arithmetic*: Users were given a non-trivial arithmetic task to be solved mentally without vocalization or making any other physical movements. Problems posed were non-repeating so that immediate answers were not apparent.
- Task 3 - *Mental letter composing*: Users are instructed to mentally compose a letter to a friend without vocalizing or making any other physical movements.

For the purpose of this present study, we had a total of 40 PSD values for each segment (or 1 second), giving a total of 480 (40 x 12 seconds) features for each recording session and each cognitive task, and a total of 1440 (480 x 3 cognitive task) features from each subject. Neural network classifier was assessed on both the training and the test validation set. 960 data were randomly taken from the 1440 data extracted using FFT-PSD method and used for training the NN, and the remaining 480 data were kept aside and used for testing each of 4 combinations pairs of cognitive tasks for each subject after each training epoch. Selection of the training data is chosen randomly. The procedures implied a randomized 10-fold cross-validation. The class distribution numbers of the samples in the training and test data set training for each subject after pre-processing are shown in Table 1.

Prior to the NN process, the training and testing samples are normalised from 0 to 1 using binary normalization algorithm[9]. Training was conducted by varying the hidden layer nodes and then calculating the offline classification error. In the case of this study, Levenberg-Marquardt back-propagation algorithm popularized by [10] was used to find a local minimum of the error function of the network. The best approach to find the optimal number of hidden units was by *trial and error*. Table II shown that a reasonable number of hidden units, with testing error tolerance value of 0.05 and better learning performance rate of 0.0001, were found between 5 and 12, and we recommend 10. Performances were not good if the numbers are less than 5 while larger than 12 has no significant decrease in the training error. Training is conducted (or the algorithm is assumed to have converged) until the average error falls below 0.0001 or reaches a maximum iteration limit of 10000.

Next, we test validation by using samples from test dataset features. By trial and error, 7 hidden nodes were chosen. The NN tries to classify these features and the number of correct classifications is recorded. Since the EEG is classified into three cognitive tasks, we ensured that the tree outputs correspond to the cognitive tasks and are represented by unit vectors: relaxation = [1 0 0], arithmetic calculation = [0 1 0], and writing letter = [0 0 1]. Result values below 0.5 of total samples are regarded as a 0 and values above 0.5 of total samples are regarded as a 1.

Table 2. Average squared error vs. hidden units

Parameters	Values
Input Neurons	1440
Output Neurons	5 (0 and 1)
Hidden Neurons	5 - 30
Learning Rate	0.0001
Testing Error Tolerance	0.05
Maximum Epoch	10000

The performance of the electrode was evaluated in terms of percentage recognition rate of cognitive patterns that were correctly detected by the electrode and extracted by the network. The overall accuracy of cognitive task scenario from EEG data recorded using non-contact electrodes was computed and presented in Table 3, which has shown that the average values over all five subjects tested were 86.10% for the relaxation scenario, 81.55% for mathematical calculation scenario and 82.35% for writing letter scenario.

TABLE 3. Classification analysis using non-contact electrode.

	Non-contact electrode										
	Average %										
Task	Subject 1		Subject 2		Subject 3		Subject 4		Subject 5		Average %
	Hidden Neurons 5	Hidden Neurons 10	Hidden Neurons 5	Hidden Neurons 10	Hidden Neurons 5	Hidden Neurons 10	Hidden Neurons 5	Hidden Neurons 10	Hidden Neurons 5	Hidden Neurons 10	
Relaxation with closed-eyes	88	85	87	85.2	87	83.8	85	86.7	85	87	86.10
Mathematical Calculation	81	82	80.5	81	80	83.5	81	83.5	80	83	81.55
Writing Letter	82	82	82.5	81	82	84.5	81	83.5	81	84	82.35

Clearly the best classification is achieved with the wet electrode (Table 4), giving an average accuracy through all five participants of 90.10% for the relaxation scenario, 86.23% for mathematical calculation scenario and 88.35% for writing letter scenario.

TABLE 4. Classification analysis using wet electrodes.

	Wet electrode Average %										
Task	Subject 1		Subject 2		Subject 3		Subject 4		Subject 5		Average %
	Hidden Neurons 5	Hidden Neurons 10	Hidden Neurons 5	Hidden Neurons 10	Hidden Neurons 5	Hidden Neurons 10	Hidden Neurons 5	Hidden Neurons 10	Hidden Neurons 5	Hidden Neurons 10	
Relaxation with closed-eyes	89	92	89.2	91	87.8	91	89	91	90	91	90.10
Mathematical Calculation	85.2	85.7	89	84	83.6	87	87	88	86	86.8	86.23
Writing Letter	88	87	86	88	86.7	86.3	87	89	87	87.3	88.33

4. CONCLUSION

In this paper, methods using non-contact capacitive EPIC electrodes in a headset system have been proposed for effective EEG recordings and classification of the cognitive EEG signals as relaxation with eye-closed, mathematical calculation and writing letter tasks. Results could show that our proposed recording technique is able to acquire quality EEG signals at different conditions. However, there is lack of optimal effectiveness and efficiency of the proposed non-contact electrode in recording cognitive states in comparison with wet electrode. This is because the PSD features extracted using FFT technique constitutes a high dimensional vector (1440 features from three different cognitive states recorded) that contains information pertinent to the classification accuracy of electrode in recording cognitive states, as well as irrelevant components. A novel EEG signal classification method is needed which will be presented in our future work.

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