

Reducing the Noise Level of EEG Signal Acquisition through Reconfiguration of Dry Contact Electrodes

Viswam Nathan and Roozbeh Jafari
Electrical Engineering Department
University of Texas at Dallas
Richardson, TX - USA
{viswamnathan,rjafari}@utdallas.edu

Abstract—Dry EEG electrodes enhance the convenience and wearability of brain computer interface (BCI) systems, but the noise induced due to the skin electrode interface reduces the signal quality compared to that of wet electrodes. In this work, we analyzed a popular dry electrode design that incorporates several ‘finger’ shaped contacts and show how the noise level can be reduced by estimating the contact quality of each finger and reconfiguring the electrode accordingly. We designed custom electrodes for this analysis and showed the differences in skin interface noise among fingers of the same electrode. Finally, we showed how eliminating the signals from one of more noisy fingers can lead to better correlation with an ideal wet electrode and reduce the amount of noise by $1.6\mu\text{V}$ on average, which constitutes 11% of the EEG signal.

Keywords—Dry contact EEG; Skin electrode noise;

I. INTRODUCTION

Brain computer interface (BCI) is a communication modality that has several applications both in the medical [1] and commercial fields [2]. BCIs are based on electroencephalography (EEG) systems that capture the brain activity using electrodes placed on the scalp.

Dry electrodes are more convenient than their wet gel-based counterparts but are also more susceptible to noise due to the high impedance contact. This noise can come from several sources including motion artifacts, thermal noise and half-cell effect at the skin-electrode interface [3, 4]. In particular, we look at the finger-based dry contact which has been implemented in several previous works [5-7]. Each electrode has a number of resistive contacts shaped like ‘fingers’ intended to penetrate through the hair and make contact with the scalp. Due to the non-homogenous nature of the contact of this electrode, as well as variations in scalp surface caused by sweat and hair, it can be reasonably assumed that the individual fingers on an electrode each have differing contacts and hence also differing amounts of noise. Nevertheless, in these electrodes, the fingers are always connected together and the signals are sent through a single channel. Our hypothesis is that the overall noise level for the electrode may be reduced by dynamically reconfiguring the electrode to exclude one or more noisy fingers from the circuit and only retain the signals from the fingers with sufficiently good contact.

The contributions of this work are as follows:

- A custom electrode was built to isolate and analyze signals acquired from each individual finger.

- The nature and properties of the skin interface noise that causes differences between fingers are highlighted.
- We introduce a method to generate and analyze the mixed signals from different combinations of fingers and show that the overall noise can be reduced by using only an optimum subset of fingers

II. SYSTEM DESCRIPTION

A. EEG Acquisition Board

The platform used to acquire the EEG signals is a custom PCB designed by our lab that uses the TI ADS1299 analog front end for EEG, an MSP430 microcontroller and a Bluetooth module for wireless data transmission.

B. Individual Finger Channel (IFC) Electrode

In order to analyze the local noise effects for each finger contact of the EEG electrode, we built a custom electrode that isolated the signals from each finger into separate channels. The electrode built for this purpose (Fig. 1) consists of 8 fingers arranged evenly spaced in a circle of radius 0.72cm. Each gold-plated finger has a height of 0.55cm and is spring loaded. The signal from each finger is immediately buffered before being sent through the cables to eliminate susceptibility to cable motion artifacts and 50/60Hz interference. The schematics in Fig 3 (a) and 3 (b) illustrate the difference between a traditional finger-based electrode [5-7] and this custom individual finger channel (IFC) electrode respectively.



Figure 1 – IFC electrode front and back

Our hypothesis is that the overall signal from the traditional electrode in Figure 3 (a) could be improved by rejecting the individual signals from one or more fingers in the circuit if they are picking up too much noise. Using an estimate of the impedance on each finger, we can generate the mixed signal that would be obtained from any combination of fingers on the IFC electrode. This can be used to test the primary hypothesis, and the methods to do so are described in detail in Section III.

C. Multiplexer (MUX) Electrode

In order to validate the analysis from the IFC electrode, we also designed a MUX electrode that can actually switch between using any combination of 8 fingers using an 8:1 MUX. Fig. 2 and Fig. 3 (c) show images of the electrode and the circuit schematic respectively.



Figure 2 – MUX Electrode front and back

A key contrast with the IFC electrode is that different combinations of MUX electrode fingers cannot be uniformly compared to each other due to the time delay involved in switching between the different combinations. This is an issue because the EEG signals they are measuring as well as the noise levels are non-stationary and always changing over time.

D. Common Mode Contact Quality Measure

In our system, a periodic square wave of known out-of-band frequency 61Hz is added to the common mode of each channel. The power of this signal at the output indicates the amount of mismatch between the signal and reference impedances in each channel as shown in [8]. In our experiments, the same wet gel patch with low impedance contact is used as the reference for all channels. So the power of this common mode frequency at the output of each channel is directly proportional to the impedance faced by the dry electrode finger in that channel. This in turn is used to compute the impedance on each finger.

III. METHODS AND EXPERIMENTS

A. IFC Electrode Combination Simulation

In our experiments, a wet electrode was placed right next to the IFC electrode to provide a ground truth signal. The noise on the wet electrode was assumed to be negligible and it is considered an ideal electrode. This is not strictly true since any electrode will be subject to some amount of noise, but we can safely assume that the amount of noise on the wet electrode is much lower than that on dry contacts and it is the best baseline available for EEG. Therefore, for each set of signals we have:

$$NoiseRMS_i = FingerRMS_i - WetRMS \quad (1)$$

Where,

i indicates a given finger on the electrode

$FingerRMS_i$ is the root mean square (RMS) of the signals from Finger i

$WetRMS$ is RMS of corresponding signals from wet electrode

$NoiseRMS_i$ is the RMS noise magnitude for Finger i

In the traditional finger electrode, we can model the finger contacts as impedances connected in parallel. Using the contact quality measure, we can obtain the impedance Z_i for each finger. Then for any given combination of fingers, we can calculate the contribution of each finger to the resulting parallel circuit. For example, for Fingers 1, 2 and 3 in parallel, the contribution fraction of Finger 1 is given by:

$$C_1 = \frac{Z_2 \parallel Z_3}{Z_1 + (Z_2 \parallel Z_3)} \quad (2)$$

In truth, the impedance is composed of both a resistance and capacitance so it would be frequency dependent; but we are only interested in the low frequency region where the electrode-skin interface noise, which is $1/f$ in nature [3, 4], would dominate. Therefore, we can ignore the effect of the capacitance. Once we have the contribution fractions of each finger in a given combination, we can compute the overall RMS noise power for that finger combination as:

$$\sqrt{(C_1 \times NoiseRMS_1)^2 + \dots + (C_n \times NoiseRMS_n)^2} \quad (3)$$

Where,

C_n is the contribution of finger n in the current combination

$NoiseRMS_n$ is the RMS noise magnitude of individual finger n defined earlier

Similarly, we can also estimate the overall EEG signal, as opposed to just the noise, by applying the same contribution fraction on the signals from any combination of fingers:

$$Signal_x = C_1 \times Finger_1 + \dots + C_n \times Finger_n \quad (4)$$

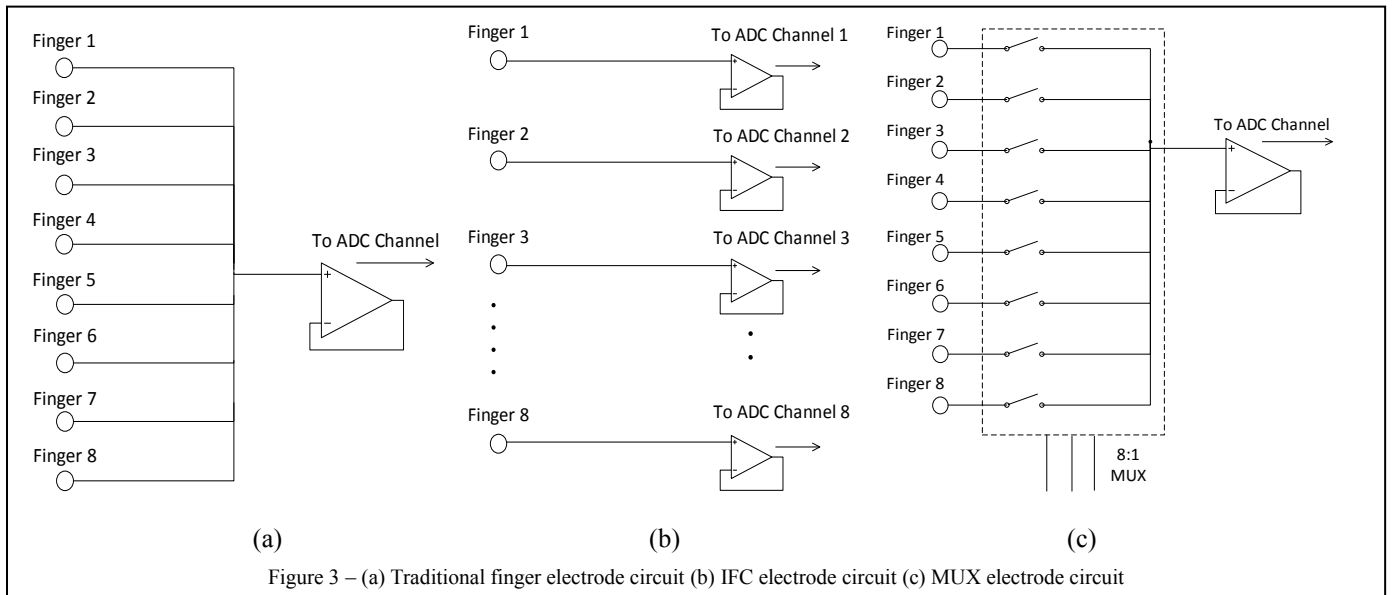


Figure 3 – (a) Traditional finger electrode circuit (b) IFC electrode circuit (c) MUX electrode circuit

Where,

$Signal_x$ is the mixed EEG signal for finger combination x

C_n is the contribution of finger n in the current combination

$Finger_n$ is the time domain EEG signal from Finger n

B. Experimental Setup

Alpha rhythms are strong EEG waveforms with known characteristics observed when a subject closes his/her eyes [9]. This EEG response can be recorded on almost all parts of the scalp. This allowed us to use a wet electrode as an ideal electrode placed on the forehead in a region with no hair to pick up the alpha. The IFC electrode is placed right next to the wet electrode in a region with hair. We can safely assume that the EEG alpha signal will be almost identical between the two electrodes at this distance [7], but at the same time the fingers on the IFC electrode will pick up varying amounts of noise due to high impedance contact. Data was collected from 3 subjects with two sessions per subject. Each session involved 20 trials of about 10 seconds of eyes-closed alpha.

IV. RESULTS AND ANALYSIS

A. Differences in noise between fingers

We plotted the power spectrum of the signals from each of the fingers on the IFC electrode as well as the signals from the wet electrode. An illustrative case for one session on Subject 1 is shown in Figure 4. Only 7 fingers of the IFC electrode were used since the 8th channel of the EEG acquisition board was reserved for the clean signals from the wet electrode. Also provided in the figure is a ranking of the fingers according to the contact quality measure described in Section II D.

Evidently there are significant differences in the frequency spectrum, with at least four fingers – Fingers 2, 3, 4 and 5 – showing significantly higher noise levels compared to the others. The wet electrode, as expected, has the least amount of noise and hence the lowest power as well. The peak at approximately 10Hz corresponds to the EEG response in the state of alpha. Among the three ‘good’ fingers - Fingers 6, 7 and 8 - the frequency response is mostly overlapped with that of the wet electrode in the higher frequencies, but there is a noticeable separation in the lower frequencies. This confirms that the noise experienced by the dry electrode fingers is 1/f in nature, which agrees with previous findings on skin interface noise [3, 4]. Another observation is that the fingers with higher noise also showed worse contact quality according to the common mode measure that we introduced. This confirms that

the noise is related to the impedance of the contact.

B. Noise analysis and correlation with wet electrode

On the IFC electrode, the mixed signals from all possible combinations of fingers were exhaustively generated using the techniques described in Section III A. The Noise RMS for each of these combinations of fingers was generated using Equation (3). For all subjects and sessions there were always several combinations better than the ‘all fingers’ combination in terms of noise magnitude. The top four combinations in terms of noise magnitude as well as the combination corresponding to all fingers, averaged across all sessions and subjects are shown in Table I. It must be noted that ‘Best Combination #1’ corresponds to the averaged noise magnitude from the very best combination from each session, but the identity and number of fingers that correspond to the ‘best combination’ is different for different subjects and sessions due to the varying contact of the electrode.

Table I: Average RMS Noise magnitude for best finger combinations compared with ‘all fingers’ combination

Finger Combinations	Average RMS Noise magnitude (μV)
Best Combination #1	1.929
Best Combination #2	1.949
Best Combination #3	2.002
Best Combination #4	2.025
All Fingers	3.539

We can see that all of the listed combinations show considerably lower noise level compared to the default ‘All Fingers’ case. When comparing the averaged best combination on each subject to the corresponding RMS noise on the ‘all fingers’ case, the improvement is about 1.6 μV . To put this in context, we can assume the wet electrode signal to be ideal and calculate the RMS of this to estimate the magnitude of the true EEG signal. On average, the RMS magnitude of the wet signal was 14.46 μV . This means that choosing the best combination of fingers on the dry electrode can reduce the amount of noise by about 11%. This is also a statistically significant trend, as proved by the fact that a one-sided paired t-test between the noise from the best combination of fingers and the noise from the ‘all fingers’ case showed a p-value < 0.05 for 20 trials, thus invalidating the null hypothesis that choosing fewer fingers does not reduce the noise.

We also generated the overall signal from each of the combinations as described by Equation (4). Signals from finger combinations with lower noise are expected to correlate better with the clean wet signal in the time domain. Again, for every

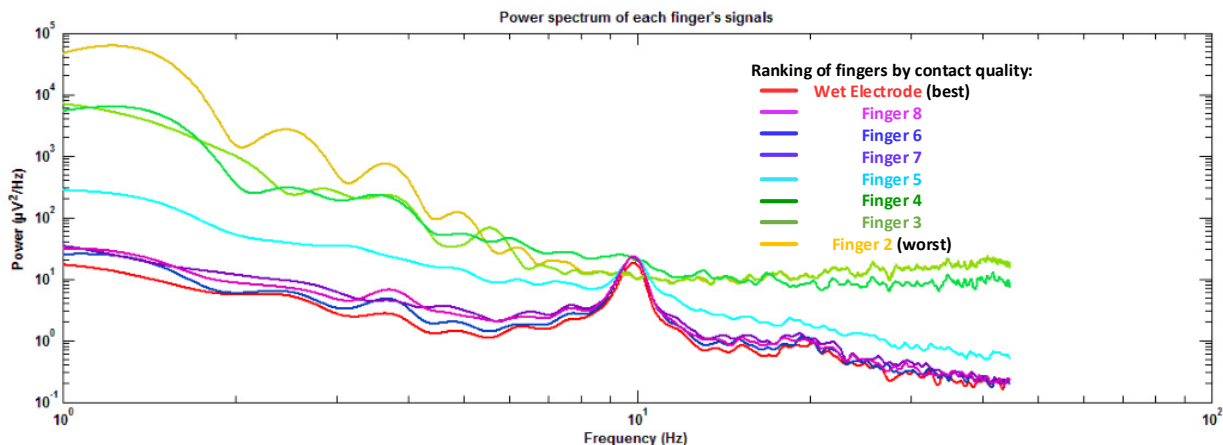


Figure 4 – Log scale plot of power spectrum from each of the fingers of IFC electrode and wet electrode

session of data there were a few combinations of fingers that showed better correlation than the ‘all fingers’ case. The averaged correlation coefficients for the best four combinations of fingers, as well as the combination with all fingers, across all subjects and sessions are shown in Table II. On average, the improvement in correlation with the wet electrode for each session was about 7.2% when using the best subset of fingers.

Table II: Average correlation coefficient with wet electrode for best finger combinations compared with ‘all fingers’ combination

Finger Combinations	Average Cross Correlation Coefficient
Best Combination #1	0.863
Best Combination #2	0.860
Best Combination #3	0.856
Best Combination #4	0.856
All Fingers	0.810

C. MUX Electrode Experiments

We aimed at validating some of these findings through experiments on the MUX electrode, where we can directly obtain signals from different combinations of fingers without the need for mixing based on electrode-skin impedances. The challenge with this electrode is the selection of an optimum finger combination without the ability to uniformly compare all the different combinations for the same EEG signals. Nevertheless, the results of the IFC electrode showed that the better finger combinations tend to exclude the fingers which had a bad contact according to the contact quality measure. This was used as a guide to select and try three different combinations during the course of the experiment for each of the subjects. Just as for the IFC electrode, a wet electrode was placed near the MUX electrode on the forehead. Once a finger combination was picked, it was alternated with the default ‘all-finger’ combination on every other trial. This allowed us to bring the two configurations as close as possible in time and compare their relative performance.

For each of the three subjects, at least one of the attempted combinations with fewer fingers showed better performance in terms of average correlation with the wet electrode, as shown in Table III. These were also all statistically significant performance improvements over the 15 trials of each session, with p-values < 0.05 in one-sided paired t-tests with the correlation coefficients of the nearest ‘all fingers’ trials.

Table III: Performance comparison between selected MUX combinations vs the ‘all fingers’ combination for all three subjects

Subject	Average Correlation Coefficient (custom finger combination)	Average Correlation Coefficient (all 8 fingers selected)	p-value from one-sided paired t-test
Subject 1 Combo 1	0.903 (4 out of 8 fingers)	0.877 (all 8 fingers)	0.0297
Subject 2 Combo 1	0.951 (3 out of 8 fingers)	0.935 (all 8 fingers)	0.0086
Subject 2 Combo 2	0.962 (4 out of 8 fingers)	0.939 (all 8 fingers)	0.0151
Subject 3 Combo 1	0.912 (2 out of 8 fingers)	0.882 (all 8 fingers)	0.0425

However, these combinations were found somewhat heuristically. In order to more extensively validate performance improvement on the MUX electrode we need to first overcome two challenges. Firstly, there is no a priori guarantee that the combination being selected for comparison is actually better

than the ‘all fingers’ scenario. Exhaustively trying all possible combinations is not an option. Secondly, the strength of the alpha response on a given subject may fluctuate during the course of one experiment. So any effort to validate a combination of fingers, in terms of performance over the default ‘all fingers’ case, may be compromised due to the changing conditions. In other words the noise level of the two configurations cannot be compared uniformly if the desired signal level itself is changing dynamically. Overcoming both of these challenges and developing a real-time automatically reconfiguring MUX electrode will constitute our future work.

V. CONCLUSIONS

In this work, we investigated the possibility of reducing the noise level of EEG signals by reconfiguration of finger-based dry electrodes. A custom electrode was built and served as a test platform to isolate and analyze the signals from each individual finger on an electrode. We observed significant differences in the noise levels across different fingers on the same electrode, and confirmed previous findings on the nature of the skin-electrode interface noise. Mixed signals from different combinations of fingers were generated using this electrode, and we observed that using the signals from only a subset of the available fingers could reduce the amount of noise, by 1.6 μ V on average, due to the exclusion of noisy fingers. An initial validation of this conclusion was provided using an actual reconfigurable electrode.

ACKNOWLEDGMENT

This work was supported in part by the Semiconductor Research Corporation, task # 1836.103 through the Texas Analog Center of Excellence (TxACE). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding organizations.

REFERENCES

- [1] E. W. Sellers, T. M. Vaughan, and J. R. Wolpaw, “A brain-computer interface for long-term independent home use,” *Amyotrophic Lateral Sclerosis*, vol. 11, no. 5, pp. 449–455, 2010. PMID: 20583947.
- [2] H.-J. Hwang, J.-H. Lim, Y.-J. Jung, H. Choi, S. W. Lee, and C.-H. Im, “Development of an ssvp-based {BCI} spelling system adopting a qwerty-style {LED} keyboard,” *Journal of Neuroscience Methods*, vol. 208, no. 1, pp. 59–65, 2012.
- [3] E. Huigen, “Noise in biopotential recording using surface electrodes,” Master’s thesis, University of Amsterdam, 2000.
- [4] Y. Chi, T.-P. Jung, and G. Cauwenberghs, “Dry-contact and noncontact biopotential electrodes: Methodological review,” *Biomedical Engineering, IEEE Reviews in*, vol. 3, pp. 106–119, 2010.
- [5] L.-D. Liao, I.-J. Wang, S.-F. Chen, J.-Y. Chang, and C.-T. Lin, “Design, fabrication and experimental validation of a novel dry-contact sensor for measuring electroencephalography signals without skin preparation,” *Sensors*, vol. 11, no. 6, pp. 5819–5834, 2011.
- [6] G. Edlinger, G. Krausz, and C. Guger, “A dry electrode concept for smr, p300 and ssvp based bcis,” in *Complex Medical Engineering (CME), 2012 ICME International Conference on*, pp. 186–190, July 2012.
- [7] R. Matthews, N. J. McDonald, H. Anumula, J. Woodward, P. J. Turner, M. A. Steindorf, K. Chang, and J. M. Pendleton, “Novel hybrid bioelectrodes for ambulatory zero-prep eeg measurements using multi-channel wireless eeg system,” in *Proceedings of the 3rd International Conference on Foundations of Augmented Cognition, FAC’07*, (Berlin, Heidelberg), pp. 137–146, Springer-Verlag, 2007.
- [8] T. Degen and H. Jackel, “Continuous monitoring of electrode–skin impedance mismatch during bioelectric recordings,” *Biomedical Engineering, IEEE Transactions on*, vol. 55, pp. 1711–1715, June 2008.
- [9] T. Sullivan, S. Deiss, T.-P. Jung, and G. Cauwenberghs, “A brain-machine interface using dry-contact, low-noise eeg sensors,” in *Circuits and Systems, 2008. ISCAS 2008. IEEE International Symposium on*, pp. 1986–1989, May 2008.