NORMALIZED MUTUAL INFORMATION IN PHANTOM MODEL AND HUMAN ELECTROENCEPHALOGRAM DATA FOR EMULATION OF CONVENTIONAL DISC ELECTRODE VIA THE OUTER RING OF TRIPOLAR CONCENTRIC RING ELECTRODE

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ABSTRACT

With some of the noninvasive electrophysiological measurement applications benefiting from simultaneous collection of data via both conventional disc electrodes and concentric ring electrodes, an emulation of the former by the outer ring of the latter was previously proposed and has since been used widely. Its effectiveness was validated using linear time and frequency domain signal synchrony measures (cross-correlation and coherence respectively) on both phantom model data and resting electroencephalogram from six healthy human subjects. However, application of a nonlinear signal synchrony measure (normalized mutual information) in this study resulted in mean values of less than 0.7 on both phantom model and human electroencephalogram datasets indicating that the outer ring of a tripolar concentric ring electrode may not be as suitable as an emulation of the disc electrode as previously suggested. Therefore, alternative options like the central disc or the middle ring will need to be assessed in the future work.

Index Terms— Electroencephalogram, synchrony, normalized mutual information, emulation, tripolar, concentric ring electrode, t-Lead, t-Interface, CREmedical

1. INTRODUCTION

Concentric ring electrodes (CREs) are noninvasive wearable sensors that allow the measurement of electrophysiological signals from organs like brain or heart to advance research involving brain-computer interface [1], [2], [3] and high frequency activity using source localization [4] in epilepsy patient data or moment of activation isochronal mapping [5] and sleep [6] in healthy human subject data. The CREs have the ability to estimate the surface Laplacian at each individual electrode by combining differential voltages between the central disc and the rings into a weighted linear combination. Finally, t-Lead electrodes (CREmedical, Kingston, RI) are commercial tripolar CREs (TCREs, Fig. 1, A) that have been used in numerous studies that include both older animal model based experiments like [7], [8] and recent human data based ones like [3], [9].

Some of CRE applications may still benefit from recording simultaneously from both CREs and conventional disc electrodes (Fig. 1, B). For example, in [10], simultaneous recordings of electroencephalogram (EEG) via disc electrodes and Laplacian estimate signals via TCREs with dimensions identical to the ones of t-Lead, from human patients with epilepsy was performed. This approach allowed a direct comparison between two sensor modalities for seizure onset detection. In [10] TCREs were placed directly behind disc electrodes in the standard 10-20 system locations. Disadvantages of this approach are two-fold. First, two sets of signals were not recorded at the exact same locations. Second, additional hardware was necessary for this approach, as simultaneous recordings via two electrode modalities required two different recording systems working at the same time which may result in issues with time synchronization of the resulting sets of signals.

Because of this, in the past, emulation of the disc electrode was proposed and assessed on both phantom model and human EEG data via either the outer ring of a TCRE or a TCRE with shorted recording surfaces. First, two emulation options were tested against the disc electrode on phantom model data using time domain signal synchrony measure (cross-correlation) [11]. Zero lag cross-correlation for the outer ring was equal to 0.9744 ± 0.0121 (mean ± standard deviation) which was statistically significantly (p = 0.009) higher than 0.9445 ± 0.0281 obtained for shorted recording surfaces. Therefore, only the outer ring (later termed eEEG for emulation of EEG via disc electrode) has been used in all future experiments. In those experiments on human EEG data, cross-correlation of 0.9905 ± 0.0065 was obtained [11]. Moreover, frequency domain signal synchrony measure (coherence) has also been applied resulting in 0.9818 ± 0.0133 [12]. Similar results were later obtained on a different human EEG dataset with all mean correlation and coherence values above 0.99 [13]. Since then multiple studies relied on the outer ring of a TCRE like t-Lead for emulation of EEG via disc electrode including [3], [14], [15], [16], [17], [18]. For example, t-Interface preamplifiers (2-Channel or 20-

Channel, CREmedical, Kingston, RI) offer two output signals for each t-Lead input channel: Laplacian estimate and eEEG.

Even though results in [11], [12], [13] suggested outer ring/eEEG to be effective as emulation of the disc electrode, their main limitation was that only linear signal synchrony measures (correlation and coherence) were used. This study addresses said limitation by adding a nonlinear signal synchrony measure (normalized mutual information, NMI) on both phantom model and human EEG data adopted from [11], [12]. For phantom model data, two comparison pairs of signals were assessed including outer ring versus disc electrode and TCRE with shorted recording surfaces versus disc electrode. For human EEG data, only the outer ring versus the disc electrode pair was assessed since shorted TCRE was not included into the respective data collection. Obtained results (mean NMI values of less than 0.7 for both datasets) indicate that the outer ring of a TCRE may not be as suitable as an emulation of the disc electrode as previously suggested in [11], [12], [13].

2. METHODS

Fig. 1. Tripolar concentric ring electrode with dimensions identical to t-Lead from CREmedical (A) and conventional disc electrode (B).

2.1. Phantom Model Data

The phantom model dataset was adopted from [11]. Three electrodes were included in data collection: the disc electrode and two modified TCREs with dimensions identical to t-Lead electrode from CREmedical, one connected as the outer ring only and the other one as the shorted disc i.e. its three recording surfaces were shorted together. All three electrodes were placed on a copper plate covered by a 3mm layer of Ten20 EEG conductive paste (Weaver and Company, Aurora, CO). The copper plate comprised of a single-sided copper cladded printed circuit board that was used as a cathode. A smaller round copper plate, used as an anode, was located and oriented centrally in such a way that three electrodes could be positioned across two perpendicular diameters of the anode circle at a constant distance of 2mm. Both the cathode and anode were connected to a signal generator producing a sinusoid with amplitude of 2.5V and frequency of 30Hz. The three electrode signals were digitized with sampling frequency of 1000Hz at 16-bit using a USB-2527 data acquisition card (Measurement Computing, Norton, MA). The duration of all the recordings was kept at 30s. A series of six recordings corresponded to six combinations of possible locations of the three electrodes at three different positions around the circular anode. A total of ten series was recorded to improve statistical validity of obtained results. All possible positioning combinations at each series of recordings were used to balance out potential variability due to electrode location. The order of series of recordings was randomized in each series to minimize the potential effect of the temporal factor. Any corrosive buildup from the cathode and anode copper plates was cleaned after each series of recordings.

2.2 Human EEG Data

The EEG dataset was adopted from [11], [12]. To reduce movement related artifacts the subjects were instructed to remain seated and motionless to record the resting EEG of six healthy human subjects (ages 24-40, one female). Skin-to-electrode impedances were kept below 5kΩ. The TCRE (dimensions identical to t-Lead electrode from CREmedical) signals were preamplified using a custom preamplifier with a gain of 6 and both signals were band pass filtered (0.1-100Hz) and recorded at 1200 samples per second using a gUSB amplifier with a normalized unit gain (g.tec medical engineering GmbH, Schiedlberg, Austria). The resulting data was segmented into non overlapping 10s yielding 173 segments total and a total duration of 1730s. Some of the monopolar/recording surface (e.g. from the outer ring) and differential (middle ring minus central disc and outer ring minus central disc) signals from both the TCREs and conventional disc electrodes were simultaneously recorded using the standard 10-20 system at location P4 with the right mastoid process being the reference and ground. Following the clinical standard for EEG recordings the frequency range selected for signal processing using Matlab (Mathworks, Natick, MA) digital filtering (zero-phase fifth-order Butterworth) was band of 1-100Hz with 60Hz notch active to reduce noise.

2.3 Normalized Mutual Information

Common information between signals was assessed via NMI. NMI in probability and information theory expresses the mutual dependence between two random variables and has been used in several EEG applications [19], [20], [21], [22]. Based on Shannon entropy mutual information is computed as in (1):

$$MI(X;Y) = \sum_{x_i y_j} P_{X,Y}(x_i, y_j) log_2 \frac{P_{X,Y}(x_i, y_j)}{P_X(x_i) P_Y(y_j)} \quad (1)$$

where P_X and P_Y are the probability distributions of two signals and $P_{X,Y}$ is their joint probability distribution. P_X, P_Y, and $P_{X,Y}$ were obtained by computing the histograms of two signals and their joint histogram, respectively, for *b* bins and dividing them by the number of signal samples (*N*). Value of *b* was determined by the Rice's rule:

$$b = \lceil 2\sqrt[3]{N} \rceil \quad (2)$$

To set the range of $MI(X;Y)$ values to that from 0 to 1, NMI was used with four different normalization approaches (minimum, maximum, arithmetic, and geometric) [23] and it was calculated for all 173 10s signal segments via Matlab implementation that has been adopted from [24]. The minimum method to normalize the mutual information is to divide it by the minimum of individual signal entropies [23]. To measure the maximum NMI mutual information is divided by the maximum of individual signal entropies [23]. Measuring the arithmetic NMI between two signals involves dividing mutual information by the arithmetic mean of the two individual signal entropies [23]. To measure the geometric NMI mutual information was divided by the square root of the product of the individual signal entropies [23].

3. RESULTS

3.1. Phantom Model Data

The obtained values for NMI measure comparing signals between the outer ring of a TCRE versus disc electrode and between the TCRE with shorted recording surfaces versus disc electrode using different normalization approaches (geometric, arithmetic, maximum, and minimum) on phantom model data are presented in Table 1. Statistical analysis was performed by first applying the Shapiro-Wilk normality test to all the NMI values (sample size n = 60) obtained for each emulation option. Since only the NMI values corresponding to the TCRE with shorted recording surfaces were normally distributed (p = 0.0583) while the ones corresponding to the outer ring of a TCRE were not (p < 0.001) the nonparametric Mann–Whitney U test was applied with the alternative hypothesis of two sample means being not equal (p = 0.00024) confirming statistical significance of the difference between two emulation options.

Table 1. Signal comparisons using NMI with four different normalization approaches on phantom model data.

Signals being compared	Normalized mutual information (mean ± standard deviation)			
	geometric	arithmetic	maximum	minimum
Outer ring versus disc electrode	0.679 ± 0.0348	0.679 ± 0.0348	0.675 ± 0.0355	0.683 ± 0.0341
Shorted TCRE versus disc electrode	0.634 ± 0.0268	0.634 ± 0.0268	0.629 ± 0.0279	0.64 ± 0.0257

3.2 Human EEG Data

The obtained values for NMI measure comparing signals between the outer ring of a TCRE versus the disc electrode using different normalization approaches (geometric, arithmetic, maximum, and minimum) on human EEG data are presented in Table 2.

Table 2. Signal comparisons using NMI with four different normalization approaches on human EEG data.

Signals being compared	Normalized mutual information (mean ± standard deviation)			
	geometric	arithmetic	maximum	minimum
Outer ring versus disc electrode	0.652 ± 0.0742	0.652 ± 0.0743	0.649 ± 0.0752	0.654 ± 0.0733

4. DISCUSSION

This study assessed a nonlinear signal synchrony measure (NMI) in the important task of emulating the conventional disc electrode with a TCRE for the first time. Obtained results for comparison between the outer ring of a TCRE and conventional disc electrode are reasonably consistent between the phantom model (Table 1) and human EEG (Table 2) data. They also demonstrate consistency between the four assessed normalization approaches for all signal comparisons and both datasets. Moreover, NMI results on phantom model data suggested that the outer ring of a TCRE is a better emulation of a disc electrode than the TCRE with shorted recording surfaces is due to statistically significant difference in the respective NMI values (p = 0.00024) which is consistent with previous results based on linear time domain signal synchrony measure (cross-correlation) on the same dataset [11]. However, mean NMI values of less than 0.7 obtained on both datasets indicate that the outer ring of a TCRE may not be as effective as an emulation of a disc electrode as previously suggested in [11], [12], [13]. Therefore, the main direction of future work based on this study is to assess alternative options like the central disc or the middle ring of a TCRE using NMI to compare their performance as disc electrode emulations to that of the outer ring.

5. ACKNOWLEDGMENTS

This work was supported by the National Science Foundation (NSF) Division of Human Resource Development (HRD) Tribal Colleges and Universities Program (TCUP) award number 2212707 to O.M. The authors gratefully acknowledge Dr. Yacine Boudria for collecting the human data in [11], [12]. O.M. thanks Dr. Tetyana Baydyk (National Autonomous University of Mexico) for the constructive discussions and helpful comments.

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