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Examining Dense-Array Electroencephalographic Networks during Sleep – Partial or Non-Partial Correlations?

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ABSTRACT

Both partial and non-partial correlation methods have been utilized by researchers to construct dense-array electroencephalographic (dEEG) networks. Similarly, researchers have been using different protocols to preprocess data and minimize spurious correlations. This methodological study examined the extent to which the dEEG connectivity networks computed by the non-partial, first-order partial, and (N-2)-order/254th-order partial correlation methods resemble each other, with two autoregressive integrative moving average (ARIMA) preprocessing models and three sample lengths being taken into consideration. Data were collected from two volunteers during the last 60 seconds of the second and fourth rapid-eye-movement epochs using a 256-channel electroencephalographic system and prior to correlation analyses, were preprocessed by either ARIMA (40, 1, 1) or ARIMA (20, 1, 1) transformation. The analyses demonstrate that the partial method, even at the first-order level, can substantially suppress the overall degree of connectivity in a network. Nevertheless, the moderate-to-large rank-order correlation values comparing the similarities between the three network-construction methods casts doubt on the supposition that a network built upon partial correlations is fundamentally distinguished from that derived from non-partial correlations.

Keywords: functional connectivity, high-density EEG, partial correlation, rapid eye movement, synchronous cortical activity

INTRODUCTION

Researchers have long been studying synchronous electroencephalographic (EEG) activities as neural correlates of conscious states. Their studies have yielded some findings, which have psychological implications. Pagel (2012), for instance, provided a comprehensive review of synchronous EEG manifestations of various conscious states associated with the sleep-wake cycle,

ranging from nonattentive waking states, through to hypnosis, psychedelic experience, and dreaming. He pointed out that lucid dreaming, as suggested by its enhanced alpha and gamma rhythms associated respectively with rapid-eye-movement (REM) sleep and focused meditation, is a state characteristic of both dreaming and wakefulness. Likewise, Dimitriadis, Laskaris, Del Rio-Portilla, and Koudounis (2009) noted an EEG segregation between the fronto-central and parieto-temporal cortical regions during REM sleep, which probably reflects the functional disconnection between the waking cognition and perceptual systems.

With the advent of dense array electroencephalographic (dEEG) technology, the study of neural connectivity has been rendered far more sophisticated than a conventional connectivity study, which entails only a minimum of two intrahemispherically

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and two interhemispherically placed electrodes. A dEEG system today can gauge up to 256 channels covering almost the entire head surface, thus thoroughly visualizing the distribution of electrical potentials generated by different regions of the brain. This allows not only more proper plotting of synchronous networks during sleep but also more diverse methodologies in handling sleep EEG data. Thus far, only a few studies (e.g., Langheim, Murphy, Riedner, & Tononi, 2011; Yu, 2015a) have attempted to construct dense sleep EEG networks using time-series statistics. By plotting significant partial correlations of all 32640 possible pairs of the 256 electrodes, Langheim et al. found a cluster of positive interactions in the right parieto-occipital region during REM sleep. Yu (2015a), on the other hand, used non-partial correlations, which resulted in positive connections over the antero-fronto-central and occipito-temporo-cerebellar regions.

dEEG synchronous connectivity can be a new parameter or direction for investigating the variations in dreaming sleep. However, there are some methodological issues that should be resolved before more extensive dEEG connectivity sleep research can be conducted. This is peculiarly true when it is considered that dEEG sleep research is labor-intensive and computationally expensive in comparison with conventional polysomnography. In establishing dense EEG networks, researchers have been employing different protocols for data referencing, preprocessing, and analysis. This, at least in part, explains the differences in connectivity networks reported by different researchers. Langheim et al. (2011) referenced all data to the default electrode Cz placed at the vertex. Yu's (2014, 2015a, Yu & Li, 2018) research group instead recommended applying a common average reference (the average of all 256 or 257 electrodes) in sleep research for more accurate localization of waveforms and reducing spurious correlations. It is worth noting that both the Cz and common average referencing approaches deviate from the American Academy of Sleep and Medicine's (AASM; Iber, Ancoli-Israel, Chesson, & Quan, 2007) standard mastoid referencing.

Referencing to the mastoid electrode on either side as recommended by the AASM is inapt for network analysis in that it would create a systematic crescendo of electrical

amplitude toward the opposite side of the head. Although this bias can be corrected by averaging the two mastoid electrodes of the sensor net (average mastoid reference), Yu and Li (2018) showed that the use of the average mastoid reference would cause the methodological artifact of the two mastoid electrodes being inversely and perfectly correlated. Additionally, the average mastoid reference tends to lower the strength of correlations for the electrodes over the mastoid process and temporal bone, wherein the inferior temporal cortex is located. Utilizing the mastoid electrodes as a reference would therefore lessen the sensitivity for detecting activities over the inferior temporal region, which is believed to play an important part in the neural network of dreaming sleep (Yu, 2001a, 2006).

Langheim et al. (2011) introduced the use of Box-Jenkins autoregressive integrative moving average (ARIMA) modeling to remove the trend in each EEG time series before correlation analyses. The ARIMA modeling method can achieve stationary variance by suppressing autocorrelation structures and curtail spurious correlations resulting from the common trends or predictability of temporal structures. Langheim et al. proposed an optimal ARIMA model, which was composed of 40 AR orders ($AR = 40$), one differencing order ($I = 1$), and one MA order ($MA = 1$). Yu (2015a) observed, however, that a sizable number of time series could not be fitted by the ARIMA (40, 1, 1) model. Since the residuals for some channels could not be generated by the ARIMA (40, 1, 1) modeling, the correlations for these unfitted channels could not be computed. As Yu and Li (2018) demonstrated, this rendered subsequent connectivity analyses unreliable in that some connections between certain critical regions for sleep, such as those between the parastriate region and the occipitotemporal junction (Yu, 2001a, 2006), could not be detected. They suggested, furthermore, that the ARIMA (20, 1, 1) model might constitute an alternative for sleep EEG data preprocessing because it effectively removed time structures to the extent very much like the ARIMA (40, 1, 1) model with virtually no unfittable channels for both early and late REM periods and different sample lengths.

Pearson correlation is the most classic measure of

connectivity. Yu (2015a) applied non-partial Pearson correlations (zero-order correlation) in his study, whereas Langheim et al. (2011) computed a partial correlation coefficient for each pair of sensors with consideration of all the remaining 254 sensors (254th-order/(N-2)-order partial correlation). In their methodological studies, Jalili and Knyazeva (2011a, 2011b) introduced yet another approach and limited their computations to first-order partial correlations. Specifically, for each pair of sensors, they calculated (N-2) correlations, with the remaining sensors being partialled out one at a time; the minimum among these (N-2) values was then chosen for further analyses.

As Jalili and Knyazeva (2011a, 2011b) averred, a correlation value may derive from direct interactions between two sensors and/or indirect connections via sequential pathways or common sources. In other words, it is assumed that non-partial correlation gives an aggregate estimate of both direct and indirect connections between two sensors, partial correlation measuring direct functional connectivity. This is, however, a theoretical supposition and the direct link or true value of the correlation between two sensors is a relative rather than absolute concept. At one end of the continuum is the correlation value with all possible indirect links being controlled, at the other end being the statistical procedure which partials out the single sensor that gives the minimum correlation value among all (N-2) first-order partial correlation values. Jalili and Knyazeva (2011a, b) argued that synchronous networks built upon partial correlations fundamentally differ from those detected by non-partial correlations. This argument suggests that using different correlation methods to construct synchronous networks would give rise to distinct patterns of connections.

The study presented here aimed to examine the extent to which the first-order and (N-2)-order partial correlation methods would alter the rank-ordered pattern of sleep EEG connections computed based on non-partial correlations. If they could only suppress the overall strength of connectivity rather than alter the pattern of correlations, they might merely serve a similar function as do the preprocessing tactics for reducing spurious correlations. In addition, it should be noted that

performing partial correlations for dEEG data with the standard sampling rate of 500Hz can be very expensive in terms of computation time – approximately eight hours for 60-second data, for example. Reducing the length of each time series can substantially lower the cost of computation. Therefore, the effects of the partial and non-partial correlation methods were considered together with varied ARIMA models and lengths of time series. Specifically, it was hypothesized that correlation matrices generated using different partial/non-partial methods, ARIMA transformation models, and time lengths would share a similar pattern of relative connectivity magnitudes among sensors.

METHOD

Two volunteers' (Subject 1: male, 23 years old; Subject 2: female, 21 years old) sleep was monitored by a high-density electroencephalographic system. The sensor net is composed of 256 index electrodes, covering almost the entire head, including areas on both cheeks and around both eyes. Data were sampled at 500 Hz and were referenced to the Cz electrode. Raw EEG data that were collected during the last 60 seconds of the second (REM2) and fourth (REM4) REM episodes of the second laboratory night and were relatively devoid of ocular and other artifacts were analyzed using the MATLAB and R statistical packages. The Cz-referenced data were preprocessed by either ARIMA (40, 1, 1) or ARIMA (20, 1, 1) transformation before connectivity analyses. Pearson correlation coefficients of the 32640 pairs of electrodes (256 x 255/2) were computed using the non-partial, first-order partial, and 254th-order partial methods. After that, Spearman correlations were performed to assess the extent to which the rank orders of the Pearson correlation coefficients generated by the three methods resembled each other. Thorough comparisons of more ARIMA models in terms of their effects on subsequent connectivity analyses are available in Yu and Li's (2018) previous report. A detailed description of the current dEEG protocol can be found elsewhere (Yu, 2014, 2015a, 2015b, 2016a). The study was approved by the University Human Research Ethics Committee.

Analyses

Table 1 lists the standard AASM derivations (see Column 1, F3 to O2) and nine other electrodes placed on the neuroanatomical regions especially relevant to sleep research (see Column 1, FT7 to TP10). For example, BA37 and BA40 are neural substrates for converting dream thoughts into dream images (see Yu, 2001a, 2001b, 2003, 2006, 2007, 2016b, for the neuroanatomical correlates of dreaming sleep). Tables 2-7 presents the Pearson correlation matrices of 60-s, REM4 data obtained with these selected channels and preprocessed by ARIMA (20, 1, 1) modeling. In both Subject 1 (Tables 2 & 3) and Subject 2 (Tables 5 & 6), the first-order partial method significantly suppressed the correlations coefficients, z values ranging between 9.02 and 37.06, all p values <

.001. The effect of the 254th-order partial process (Tables 4 & 7), as compared with the first-order partial process (Tables 3 & 6), was even more robust, z values ranging between 6.5 and 39.18, all p values < .001. The magnitudes of all 254th-order partial correlations were minuscule. Nonetheless, the three correlation methods resulted in a similar pattern of relative magnitudes among the coefficients, the strongest connections being mostly clustered around P7, TP9, O1, P8, TP10, and O2.

The results for Spearman correlations are shown in Tables 8-11. The large rank-order correlation coefficients (> 0.5) indicated that varying the ARIMA parameters, the sampling rate, or even both did not substantially alter the rank-order sequence of coefficients between any two correlation matrices in both subjects and both REM stages,

Table 1. Electrode Positions and Corresponding Neuroanatomical Regions

10-20 position	Electrode number	Brodmann area	Neuroanatomical area
F3	E36	BA8	Intermediate frontal
F4	E224	BA8	Intermediate frontal
C3	E59	BA1-4	Central
C4	E183	BA1-4	Central
O1	E116	BA18	Parastriate
O2	E150	BA18	Parastriate
FT7	E62	BA47	Orbitofrontal
FT8	E211	BA47	Orbitofrontal
CP3	E66	BA40	Supramarginal
CP4	E164	BA40	Supramarginal
P7	E96	BA37	Occipitotemporal
P8	E170	BA37	Occipitotemporal
Cz	Reference	BA4	Vertex
TP9	E94	BA20, BA21	Mastoid/inferoposterior temporal
TP10	E190	BA20, BA21	Mastoid/inferoposterior temporal

Table 2. Non-Partial Correlation Matrix for Cz Referenced, ARIMA (20, 1, 1) Preprocessed, 60-s Data Extracted from Subject 1's REM4

	F3	F4	C3	C4	O1	O2	FT7	FT8	CP3	CP4	P7	P8	TP9
F4	0.330												
C3	0.320	0.162											
C4	0.193	0.313	0.128										
O1	0.229	0.193	0.281	0.241									
O2	0.188	0.209	0.199	0.292	0.420								
FT7	0.427	0.276	0.346	0.217	0.351	0.268							
FT8	0.289	0.380	0.195	0.354	0.290	0.312	0.335						
CP3	0.270	0.147	0.394	0.143	0.312	0.234	0.335	0.186					
CP4	0.170	0.258	0.143	0.395	0.258	0.325	0.209	0.332	0.155				
P7	0.284	0.196	0.348	0.225	0.469	0.357	0.401	0.278	0.377	0.229			
P8	0.204	0.243	0.188	0.338	0.363	0.422	0.272	0.361	0.204	0.351	0.318		
TP9	0.315	0.235	0.317	0.245	0.467	0.367	0.446	0.367	0.330	0.240	0.483	0.346	
TP10	0.259	0.301	0.211	0.332	0.370	0.399	0.333	0.473	0.219	0.334	0.344	0.436	0.420

Note. The 3 largest correlation coefficients are bolded.

Table 3. First-Order Partial Correlation Matrix for Cz Referenced, ARIMA (20, 1, 1) Preprocessed, 60-s Data Extracted from Subject 1's REM4

	F3	F4	C3	C4	O1	O2	FT7	FT8	CP3	CP4	P7	P8	TP9
F4	0.176												
C3	0.177	0.064											
C4	0.086	0.181	0.055										
O1	0.090	0.077	0.140	0.113									
O2	0.078	0.090	0.083	0.157	0.228								
FT7	0.239	0.121	0.203	0.094	0.169	0.120							
FT8	0.120	0.216	0.086	0.199	0.127	0.150	0.144						
CP3	0.139	0.059	0.265	0.064	0.160	0.113	0.195	0.074					
CP4	0.072	0.133	0.067	0.280	0.125	0.188	0.098	0.186	0.075				
P7	0.134	0.092	0.206	0.116	0.291	0.182	0.232	0.124	0.232	0.113			
P8	0.093	0.105	0.083	0.209	0.189	0.274	0.134	0.187	0.095	0.217	0.161		
TP9	0.148	0.103	0.178	0.113	0.280	0.185	0.256	0.191	0.183	0.112	0.298	0.178	
TP10	0.120	0.150	0.091	0.185	0.192	0.233	0.163	0.276	0.095	0.190	0.179	0.262	0.233

Note. The 3 largest correlation coefficients are bolded.

Table 4. 254th-Order Correlation Matrix for Cz Referenced, ARIMA (20, 1, 1) Preprocessed, 60-s Data Extracted from Subject 1's REM4

	F3	F4	C3	C4	O1	O2	FT7	FT8	CP3	CP4	P7	P8	TP9
F4	0.019												
C3	0.004	-0.008											
C4	0.003	0.017	-0.007										
O1	-0.009	0.004	-0.007	-0.008									
O2	0.006	0.012	-0.013	-0.015	0.002								
FT7	0.013	0.001	0.003	-0.008	0.001	-0.010							
FT8	-0.001	0.017	0.013	0.006	0.001	0.002	-0.003						
CP3	-0.004	0.006	0.049	0.000	-0.008	0.003	0.009	-0.008					
CP4	0.010	-0.002	0.009	0.049	-0.003	0.008	0.001	0.003	0.000				
P7	-0.002	-0.005	0.001	0.005	0.012	-0.006	-0.001	-0.001	0.016	-0.008			
P8	0.004	-0.009	0.002	0.013	-0.003	0.032	-0.008	-0.008	-0.004	0.012	-0.008		
TP9	-0.008	-0.014	0.007	0.007	0.016	0.002	-0.007	0.017	0.008	-0.004	0.032	0.001	
TP10	-0.001	-0.004	0.001	0.001	-0.003	0.011	-0.015	0.030	-0.006	0.006	0.004	0.025	0.013

Note. The 4 largest correlation coefficients are bolded.

Table 5. Non-Partial Correlation Matrix for Cz Referenced, ARIMA (20, 1, 1) Preprocessed, 60-s Data Extracted from Subject 2's REM4

	F3	F4	C3	C4	O1	O2	FT7	FT8	CP3	CP4	P7	P8	TP9
F4	0.377												
C3	0.396	0.278											
C4	0.298	0.418	0.263										
O1	0.288	0.253	0.327	0.306									
O2	0.274	0.296	0.271	0.360	0.482								
FT7	0.430	0.324	0.378	0.291	0.365	0.327							
FT8	0.355	0.442	0.278	0.441	0.328	0.381	0.383						
CP3	0.369	0.270	0.438	0.310	0.442	0.358	0.419	0.313					
CP4	0.269	0.359	0.260	0.437	0.328	0.381	0.283	0.413	0.308				
P7	0.345	0.286	0.362	0.316	0.545	0.440	0.425	0.351	0.470	0.322			
P8	0.299	0.343	0.276	0.425	0.439	0.560	0.338	0.454	0.349	0.434	0.426		
TP9	0.364	0.303	0.350	0.308	0.459	0.401	0.485	0.393	0.419	0.317	0.516	0.409	
TP10	0.316	0.346	0.279	0.398	0.407	0.483	0.383	0.507	0.351	0.396	0.412	0.557	0.462

Note. The 3 largest correlation coefficients are bolded.

Table 6. First-Order Partial Correlation Matrix for Cz Referenced, ARIMA (20, 1, 1) Preprocessed, 60-s Data Extracted from Subject 2's REM4

	F3	F4	C3	C4	O1	O2	FT7	FT8	CP3	CP4	P7	P8	TP9
F4	0.201												
C3	0.227	0.154											
C4	0.151	0.237	0.137										
O1	0.117	0.111	0.159	0.143									
O2	0.120	0.124	0.128	0.163	0.272								
FT7	0.238	0.155	0.205	0.144	0.169	0.157							
FT8	0.160	0.236	0.136	0.243	0.141	0.174	0.184						
CP3	0.197	0.141	0.249	0.178	0.250	0.188	0.223	0.153					
CP4	0.133	0.193	0.143	0.276	0.160	0.184	0.145	0.226	0.173				
P7	0.161	0.136	0.179	0.153	0.306	0.222	0.217	0.168	0.260	0.159			
P8	0.139	0.148	0.137	0.219	0.215	0.321	0.168	0.231	0.176	0.224	0.200		
TP9	0.168	0.133	0.160	0.139	0.230	0.195	0.236	0.177	0.197	0.150	0.262	0.198	
TP10	0.150	0.159	0.123	0.202	0.175	0.260	0.181	0.267	0.166	0.196	0.195	0.331	0.219

Note. The 3 largest correlation coefficients are bolded.

Table 7. 254th-Order Correlation Matrix for Cz Referenced, ARIMA (20, 1, 1) Preprocessed, 60-s Data Extracted from Subject 2's REM4

	F3	F4	C3	C4	O1	O2	FT7	FT8	CP3	CP4	P7	P8	TP9
F4	0.001												
C3	0.008	0.003											
C4	-0.003	0.013	-0.006										
O1	-0.008	-0.011	-0.004	-0.011									
O2	0.005	0.012	-0.004	-0.011	0.018								
FT7	-0.001	-0.004	0.002	-0.012	-0.005	0.008							
FT8	-0.003	-0.006	0.002	0.002	-0.003	-0.009	0.001						
CP3	0.003	-0.010	0.027	0.014	0.014	-0.006	0.008	-0.004					
CP4	0.002	0.009	0.004	0.036	0.001	-0.010	0.002	0.010	0.004				
P7	0.003	0.001	-0.008	0.001	0.036	-0.008	0.002	0.003	0.014	-0.005			
P8	0.003	0.001	0.008	0.017	0.002	0.046	-0.007	-0.008	-0.005	0.012	0.011		
TP9	-0.009	-0.010	-0.003	-0.004	0.008	0.005	0.004	-0.000	-0.011	0.010	0.009	0.009	
TP10	-0.002	-0.007	-0.007	0.000	-0.002	0.005	0.002	0.013	0.009	-0.004	-0.007	0.024	0.014

Note. The 3 largest correlation coefficients are bolded.

Table 8. Spearman Correlation Coefficients Comparing the 256-channel Correlation Matrices between Non-Partial and Partial Correlations (Subject 1's REM2)

	Np (20, 1, 1) 15s	1 st order (20, 1, 1) 15s	254 th order (20, 1, 1) 15s	Np (40, 1, 1) 15s	1 st order (40, 1, 1) 15s	254 th order (40, 1, 1) 15s	Np (20, 1, 1) 30s	1 st order (20, 1, 1) 30s	254 th order (20, 1, 1) 30s	Np (40, 1, 1) 30s	1 st order (40, 1, 1) 30s	254 th order (40, 1, 1) 30s	Np (20, 1, 1) 60s	1 st order (20, 1, 1) 60s	254 th order (20, 1, 1) 60s	Np (40, 1, 1) 60s	1 st order (40, 1, 1) 60s
1 st order (20, 1, 1) 15s	0.928																
254 th order (20, 1, 1) 15s	0.309	0.411															
Np (40, 1, 1) 15s	0.998	0.931	0.318														
1 st order (40, 1, 1) 15s	0.915	0.997	0.417	0.924													
254 th order (40, 1, 1) 15s	0.316	0.420	0.990	0.322	0.425												
Np (20, 1, 1) 30s	0.992	0.903	0.283	0.987	0.885	0.289											
1 st order (20, 1, 1) 30s	0.950	0.977	0.359	0.949	0.968	0.367	0.947										
254 th order (20, 1, 1) 30s	0.225	0.273	0.250	0.244	0.295	0.300	0.220	0.265									
Np (40, 1, 1) 30s	0.994	0.912	0.293	0.993	0.898	0.301	0.998	0.950	0.247								
1 st order (40, 1, 1) 30s	0.943	0.983	0.366	0.947	0.979	0.376	0.933	0.996	0.295	0.943							
254 th order (40, 1, 1) 30s	0.241	0.288	0.309	0.260	0.308	0.353	0.242	0.292	0.826	0.246	0.294						
Np (20, 1, 1) 60s	0.987	0.888	0.265	0.981	0.869	0.271	0.997	0.935	0.212	0.993	0.919	0.235					
1 st order (20, 1, 1) 60s	0.948	0.966	0.331	0.946	0.955	0.338	0.948	0.992	0.254	0.950	0.987	0.282	0.944				
254 th order (20, 1, 1) 60s	0.164	0.197	0.045	0.185	0.221	0.085	0.160	0.189	0.382	0.191	0.223	0.379	0.156	0.186			
Np (40, 1, 1) 60s	0.989	0.894	0.272	0.986	0.879	0.279	0.995	0.936	0.227	0.996	0.926	0.241	0.998	0.945	0.174		
1 st order (40, 1, 1) 60s	0.941	0.971	0.337	0.944	0.965	0.345	0.935	0.989	0.271	0.943	0.991	0.289	0.930	0.996	0.205	0.939	
254 th order (40, 1, 1) 60s	0.357	0.442	0.621	0.368	0.448	0.626	0.359	0.446	0.322	0.370	0.453	0.385	0.356	0.448	0.038	0.362	0.453

Note. Np = non-partial correlation matrix, 1st order = first-order partial correlation matrix, 254th order = N-2 partial correlation matrix, (40, 1, 1) = ARIMA (40, 1, 1) preprocessed correlation matrix, (20, 1, 1) = ARIMA (20, 1, 1) preprocessed correlation matrix, 15s = calculated based on 15-second data, 30s = calculated based on 30-second data, 60s = calculated based on 60-second data.

especially those comparing non-partial and first-order partial correlation matrices. The rank-order correlation coefficient comparing any non-partial and first-order partial correlation matrices was very large, with the overall average value of 0.938. For example, the rank-order correlation coefficient between the non-partial correlation matrix for the 15-s, ARIMA (20, 1, 1) processed data and the first-order partial correlation matrix for the 60-s, ARIMA (40, 1, 1) processed data was 0.941 in Subject 1's REM2 (see Table

8) and 0.926 in Subject2's REM4 (see Table 11). By contrast, 254th-order partial correlation matrices considerably differed from their non-partial and first-order partial counterparts. Nevertheless, most of the rank-order correlation coefficients exhibited a moderate effect size (> 0.3). The overall average rank-order correlation coefficient comparing non-partial and 254th-order partial correlation matrices was 0.316, that comparing first-order and 254th-order partial correlation matrices being 0.391.

Table 9. Spearman Correlation Coefficients Comparing the 256-channel Correlation Matrices between Non-Partial and Partial Correlations (Subject 1's REM4)

	Np (20, 1, 1) 15s	1 st order (20, 1, 1) 15s	254 th order (20, 1, 1) 15s	Np (40, 1, 1) 15s	1 st order (40, 1, 1) 15s	254 th order (40, 1, 1) 15s	Np (20, 1, 1) 30s	1 st order (20, 1, 1) 30s	254 th order (20, 1, 1) 30s	Np (40, 1, 1) 30s	1 st order (40, 1, 1) 30s	254 th order (40, 1, 1) 30s	Np (20, 1, 1) 60s	1 st order (20, 1, 1) 60s	254 th order (20, 1, 1) 60s	Np (40, 1, 1) 60s	1 st order (40, 1, 1) 60s
1 st order (20, 1, 1) 15s	0.952																
254 th order (20, 1, 1) 15s	0.344	0.414															
Np (40, 1, 1) 15s	0.998	0.951	0.360														
1 st order (40, 1, 1) 15s	0.954	0.954	0.457	0.961													
254 th order (40, 1, 1) 15s	0.331	0.431	0.961	0.338	0.424												
Np (20, 1, 1) 30s	0.993	0.959	0.311	0.990	0.937	0.311											
1 st order (20, 1, 1) 30s	0.951	0.991	0.368	0.950	0.948	0.384	0.966										
254 th order (20, 1, 1) 30s	0.373	0.431	0.784	0.391	0.482	0.744	0.365	0.436									
Np (40, 1, 1) 30s	0.991	0.960	0.324	0.991	0.942	0.325	0.998	0.968	0.381								
1 st order (40, 1, 1) 30s	0.957	0.973	0.397	0.963	0.982	0.389	0.960	0.984	0.471	0.967							
254 th order (40, 1, 1) 30s	0.358	0.450	0.746	0.376	0.450	0.771	0.366	0.455	0.957	0.374	0.457						
Np (20, 1, 1) 60s	0.977	0.950	0.283	0.969	0.909	0.291	0.987	0.954	0.329	0.982	0.936	0.340					
1 st order (20, 1, 1) 60s	0.928	0.964	0.338	0.923	0.917	0.354	0.941	0.970	0.397	0.939	0.950	0.415	0.956				
254 th order (20, 1, 1) 60s	0.382	0.435	0.645	0.399	0.485	0.606	0.374	0.440	0.808	0.389	0.473	0.767	0.356	0.443			
Np (40, 1, 1) 60s	0.974	0.952	0.299	0.970	0.914	0.304	0.986	0.955	0.347	0.984	0.942	0.355	0.999	0.956	0.375		
1 st order (40, 1, 1) 60s	0.928	0.956	0.359	0.928	0.934	0.360	0.937	0.964	0.421	0.939	0.961	0.425	0.947	0.995	0.468	0.953	
254 th order (40, 1, 1) 60s	0.368	0.456	0.604	0.377	0.447	0.627	0.376	0.460	0.761	0.388	0.463	0.795	0.368	0.466	0.954	0.375	0.468

Note. Np = non-partial correlation matrix, 1st order = first-order partial correlation matrix, 254th order = N-2 partial correlation matrix, (40, 1, 1) = ARIMA (40, 1, 1) preprocessed correlation matrix, (20, 1, 1) = ARIMA (20, 1, 1) preprocessed correlation matrix, 15s = calculated based on 15-second data, 30s = calculated based on 30-second data, 60s = calculated based on 60-second data.

Table 10. Spearman Correlation Coefficients Comparing the 256-channel Correlation Matrices between Non-Partial and Partial Correlations (Subject 2's REM2)

	Np (20, 1, 1) 15s	1 st order (20, 1, 1) 15s	254 th order (20, 1, 1) 15s	Np (40, 1, 1) 15s	1 st order (40, 1, 1) 15s	254 th order (40, 1, 1) 15s	Np (20, 1, 1) 30s	1 st order (20, 1, 1) 30s	254 th order (20, 1, 1) 30s	Np (40, 1, 1) 30s	1 st order (40, 1, 1) 30s	254 th order (40, 1, 1) 30s	Np (20, 1, 1) 60s	1 st order (20, 1, 1) 60s	254 th order (20, 1, 1) 60s	Np (40, 1, 1) 60s	1 st order (40, 1, 1) 60s
1 st order (20, 1, 1) 15s	0.960																
254 th order (20, 1, 1) 15s	0.303	0.405															
Np (40, 1, 1) 15s	0.998	0.966	0.317														
1 st order (40, 1, 1) 15s	0.955	0.997	0.411	0.961													
254 th order (40, 1, 1) 15s	0.296	0.383	0.958	0.303	0.391												
Np (20, 1, 1) 30s	0.990	0.947	0.272	0.989	0.941	0.276											
1 st order (20, 1, 1) 30s	0.939	0.973	0.345	0.945	0.972	0.340	0.951										
254 th order (20, 1, 1) 30s	0.326	0.420	0.777	0.341	0.427	0.742	0.316	0.407									
Np (40, 1, 1) 30s	0.987	0.948	0.285	0.988	0.946	0.289	0.999	0.955	0.330								
1 st order (40, 1, 1) 30s	0.931	0.968	0.353	0.940	0.971	0.349	0.944	0.998	0.415	0.951							
254 th order (40, 1, 1) 30s	0.319	0.399	0.741	0.335	0.409	0.769	0.322	0.406	0.956	0.328	0.411						
Np (20, 1, 1) 60s	0.989	0.937	0.260	0.987	0.930	0.267	0.997	0.938	0.301	0.995	0.929	0.310					
1 st order (20, 1, 1) 60s	0.958	0.973	0.322	0.961	0.969	0.324	0.968	0.989	0.376	0.971	0.984	0.381	0.964				
254 th order (20, 1, 1) 60s	0.350	0.441	0.652	0.367	0.449	0.620	0.342	0.430	0.818	0.357	0.437	0.779	0.340	0.429			
Np (40, 1, 1) 60s	0.987	0.939	0.269	0.988	0.935	0.278	0.997	0.942	0.311	0.997	0.937	0.320	0.998	0.967	0.352		
1 st order (40, 1, 1) 60s	0.950	0.969	0.327	0.958	0.970	0.331	0.962	0.989	0.382	0.969	0.989	0.388	0.956	0.997	0.436	0.963	
254 th order (40, 1, 1) 60s	0.339	0.416	0.620	0.357	0.427	0.642	0.343	0.424	0.780	0.358	0.432	0.808	0.345	0.429	0.961	0.352	0.435

Note. Np = non-partial correlation matrix, 1st order = first-order partial correlation matrix, 254th order = N-2 partial correlation matrix, (40, 1, 1) = ARIMA (40, 1, 1) preprocessed correlation matrix, (20, 1, 1) = ARIMA (20, 1, 1) preprocessed correlation matrix, 15s = calculated based on 15-second data, 30s = calculated based on 30-second data, 60s = calculated based on 60-second data.

Table 11. Spearman Correlation Coefficients Comparing the 256-channel Correlation Matrices between Non-Partial and Partial Correlations (Subject 2's REM4)

	Np (20, 1, 1) 15s	1 st order (20, 1, 1) 15s	254 th order (20, 1, 1) 15s	Np (40, 1, 1) 15s	1 st order (40, 1, 1) 15s	254 th order (40, 1, 1) 15s	Np (20, 1, 1) 30s	1 st order (20, 1, 1) 30s	254 th order (20, 1, 1) 30s	Np (40, 1, 1) 30s	1 st order (40, 1, 1) 30s	254 th order (40, 1, 1) 30s	Np (20, 1, 1) 60s	1 st order (20, 1, 1) 60s	254 th order (20, 1, 1) 60s	Np (40, 1, 1) 60s	1 st order (40, 1, 1) 60s
1 st order (20, 1, 1) 15s	0.927																
254 th order (20, 1, 1) 15s	0.318	0.400															
Np (40, 1, 1) 15s	0.998	0.928	0.323														
1 st order (40, 1, 1) 15s	0.928	0.962	0.428	0.932													
254 th order (40, 1, 1) 15s	0.304	0.408	0.961	0.308	0.402												
Np (20, 1, 1) 30s	0.992	0.915	0.284	0.989	0.899	0.280											
1 st order (20, 1, 1) 30s	0.941	0.980	0.349	0.939	0.942	0.356	0.946										
254 th order (20, 1, 1) 30s	0.346	0.413	0.777	0.351	0.446	0.735	0.335	0.416									
Np (40, 1, 1) 30s	0.991	0.916	0.290	0.991	0.902	0.286	0.999	0.946	0.341								
1 st order (40, 1, 1) 30s	0.949	0.967	0.371	0.951	0.973	0.357	0.943	0.985	0.442	0.946							
254 th order (40, 1, 1) 30s	0.328	0.421	0.742	0.334	0.415	0.765	0.328	0.424	0.959	0.334	0.425						
Np (20, 1, 1) 60s	0.973	0.911	0.268	0.968	0.884	0.269	0.983	0.942	0.314	0.980	0.932	0.314					
1 st order (20, 1, 1) 60s	0.905	0.965	0.324	0.902	0.928	0.330	0.907	0.979	0.382	0.905	0.963	0.389	0.936				
254 th order (20, 1, 1) 60s	0.365	0.427	0.647	0.370	0.459	0.608	0.354	0.430	0.814	0.360	0.455	0.773	0.351	0.436			
Np (40, 1, 1) 60s	0.986	0.924	0.274	0.986	0.900	0.275	0.995	0.952	0.321	0.996	0.946	0.321	0.999	0.934	0.360		
1 st order (40, 1, 1) 60s	0.926	0.974	0.339	0.927	0.961	0.335	0.921	0.984	0.399	0.923	0.986	0.394	0.931	0.995	0.454	0.935	
254 th order (40, 1, 1) 60s	0.348	0.436	0.616	0.353	0.430	0.633	0.349	0.439	0.779	0.356	0.441	0.805	0.356	0.448	0.961	0.357	0.448

Note. Np = non-partial correlation matrix, 1st order = first-order partial correlation matrix, 254th order = N-2 partial correlation matrix, (40, 1, 1) = ARIMA (40, 1, 1) preprocessed correlation matrix, (20, 1, 1) = ARIMA (20, 1, 1) preprocessed correlation matrix, 15s = calculated based on 15-second data, 30s = calculated based on 30-second data, 60s = calculated based on 60-second data.

DISCUSSION

The study presented here compared the dEEG connectivity matrices generated by the non-partial, first-order partial, and (N-2)-order partial correlation methods, taking two ARIMA preprocessing models and three sample lengths into consideration. The results indicate that a partial correlation process for dEEG analysis, even at the first-order level, can substantially suppress the degree of connectivity. The effect of the (N-2)-order partial process in the dEEG context is even more dramatic in that the correlation coefficients can be infinitesimal after partialling out the remaining 254 sensors. Notwithstanding the significant suppression effect, the first-order partial process does not greatly alter the pattern of the relative magnitudes among the 32640 possible connections. The first-order partial method, which involves identifying the minimum value from 254 correlation values for each of the 32640 possible connections in each dataset, necessitates computer programming. Indeed, as shown by the present analyses, the rank orderings of the non-partial and first-order partial correlation matrices are so similar that researchers may need to consider whether writing such an algorithm is cost-effective.

By contrast, the (N-2)-order partial process would yield a correlation matrix that is only moderately similar to its corresponding first-order partial and non-partial correlation matrices. This suggests that it might detect a network akin to, but not the same as, those discerned by the first-order partial and non-partial methods. Partialling out N-2 sensors in dEEG could result in improbably small coefficients; that is, a close-to-zero coefficient is unreasonable for a pair of neighboring or functionally related sensors. Accordingly, certain adjustments are necessary in further analyses, such as lowering the threshold when plotting dEEG networks. Future studies may explore the optimal number of sensors being partialled out that could produce more realistic coefficients for dEEG connectivity research.

Changing the ARIMA parameters, the sampling rate, or even both do not appear to significantly alter a dEEG network. On the one hand, researchers may, during the initial stage, search for a dEEG network using shorter time series to reduce computation time. On the other hand, however, choosing appropriate ARIMA parameters that can fit all 256 time-series data is still essential for examining synchronous dEEG activities. It should be noted that in the study presented here, the correlation coefficients were computed with the unfitted channels being

excluded. As mentioned previously, ARIMA (40, 1, 1) preprocessing may create a considerable number of unfitted channels, which may in turn lead to an underestimation of connectivity in certain neuroanatomical regions (Yu, 2015a; Yu & Li, 2018).

Non-partial correlations, theoretically, account for aggregate connectivity contributed by both direct and indirect links, partial correlations being assumed to signify direct coupling. The study presented here demonstrates, nevertheless, that even the partial

correlation procedure that controls the effects of all remaining 254 electrodes would produce a connectivity pattern that can be, to a moderate extent, matched with a network without eliminating ancillary links. Accordingly, whether a network built upon partial correlations is fundamentally different from that constructed via non-partial correlations is debatable. For large-scale dEEG studies, perhaps, non-partial correlation is probably a more feasible and effective approach.

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