Robustness of functional connectivity metrics for EEG-based personal identification over task-induced intra-class and inter-class variations

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Abstract

Growing interest is devoted to understanding in which situations and with what accuracy brain signals recorded from scalp electroencephalography (EEG) may represent unique fingerprints of individual neural activity. In this context, the present paper aims to investigate the impact of some of the most commonly used metrics to estimate functional connectivity on the ability to unveil personal distinctive patterns of inter-channel interactions. Different metrics were compared in terms of equal error rate. It is widely accepted that each connectivity metric carries specific information in respect to the underlying interactions. Experimental results on publicly available EEG recordings show that different connectivity metrics define peculiar subjective profile of connectivity and show different mechanisms to detect subject-specific patterns of inter-channel interactions. Moreover, these findings highlight that some measures are more accurate and more robust than others, regardless of the task performed by the user. Finally, it is important to consider that frequency content and spurious connectivity may still play a relevant role in determining subject-specific characteristics.

Keywords:
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1. Introduction

The investigation of subject specific human characteristics that can be used to develop robust biometric systems still represents a big challenge. In this context, growing interest is devoted to understanding how brain signals recorded from scalp electroencephalography (EEG) may represent a unique fingerprint of individual neural activity. In the last few years a huge number of works have investigated the potential role of EEG signal characteristics as biometric system (about 300 new papers in the last 10 years). A detailed literature overview of the methods proposed so far is therefore quite challenging and in any case out of the scope of the present study. Nevertheless, some attempts to summarize the state of the art was previously proposed in (Campisi and La Rocca, 2014; Khalifa et al., 2012; Del Pozo-Banos et al., 2014). In brief, it is possible to consider the approaches proposed up until now mainly organized into two fundamental categories: (i) task based and (ii) resting-state based EEG analysis. The first category is oriented on experimental setups that allow to investigate properties of the EEG signal that are strictly related to some specific stimulus. Motor (real and imagery) tasks (Yang et al., 2018), visual evoked potentials (Das et al., 2015; Palaniappan and Mandic, 2007; Armstrong et al., 2015), auditory stimuli (Light et al., 2010), imagined speech (Brigham and Kumar, 2010), eye blinking (Abo-Zahhad et al., 2016) and multiple functional brain systems (Ruiz-Blondet et al., 2016) have been proposed so far in order to elicit indi-

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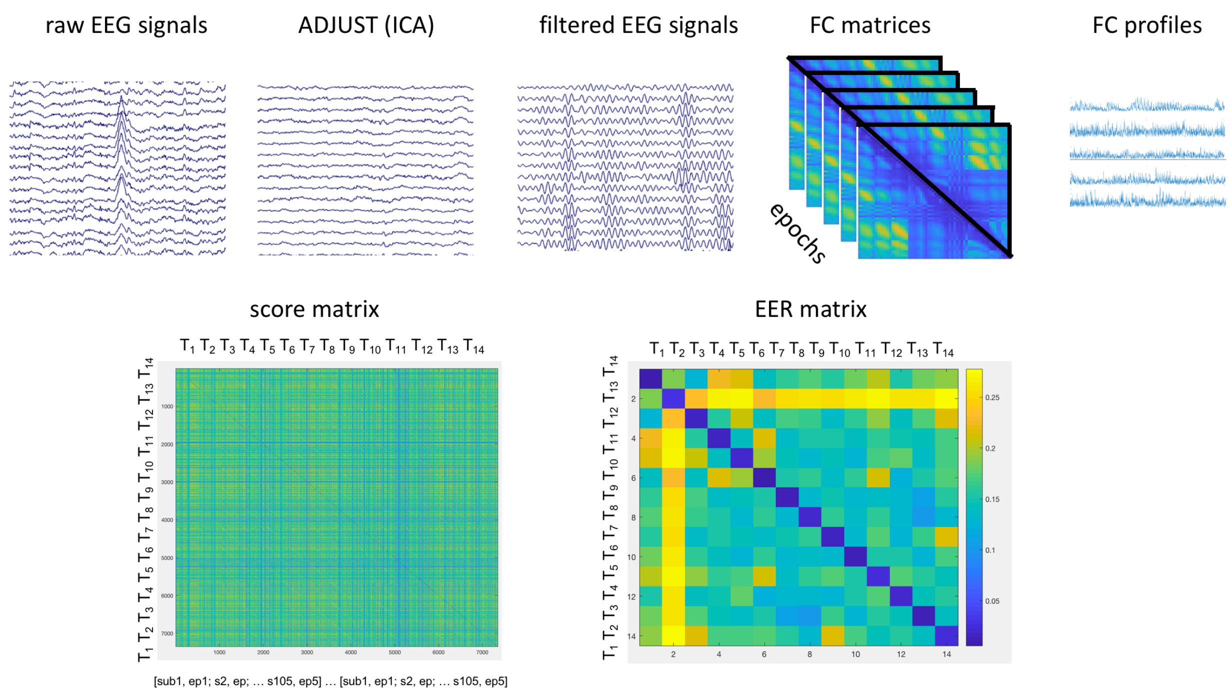

Figure 1: A schematic representation of the different steps involved in the analysis. From upper-left to bottom-right the panels represent: original raw EEG signals, artifact-free EEG traces, band-pass filtered signals, FC conenctivity matrices for each epoch, FC profiles extracted from each matrix, score matrix derived from Euclidian distance between FC profiles from all the 14 runs / 105 subjects / 5 epochs and EER matrix reporting the performance for each combination of the 14 different runs.

vidual unique responses. In contrast, the second category is mainly oriented to detect characteristic patterns of induced brain activity at rest both during eyes-closed and eyes-open. In line with the extensive use of tools from modern network science to understand brain complex organization (Stam, 2014), measures of functional connectivity (La Rocca et al., 2014; DelPozo-Banos et al., 2015; Han et al., 2015; Garau et al., 2016) and network metrics have been recently proposed (Crobe et al., 2016; Fraschini et al., 2015) as EEG-based biometric traits. Finally, multimodal approaches based on the fusion of EEG and ECG features have been also proposed (Riera et al., 2008; Barra et al., 2017). However, it seems still evident that there exists a gap between current investigations of EEG signal as neurophysiological marker and its application in personal verification systems. In particular, it is widely accepted that different metrics used to assess functional connectivity carry specific information with respect to the underlying interactions network (Kida et al., 2016). Nevertheless, it is still not clear if these metrics convey different subject specific information. Following what previously reported in (Garau et al., 2016; Fraschini et al., 2015), the present paper aims to investigate and compare the impact of some of the most commonly used techniques to estimate functional connectivity on the ability to detect personal unique distinctive features based on inter-channel interaction profiles. In order to answer this question, we focused our attention on measures based on different properties of the original signals. In particular, the following measures were included in the present study: (i) the Correlation Coefficient (CC), representing a sort of (spurious) connectivity baseline; (ii) the Phase Lag Index (PLI) (Stam et al., 2007), which quantifies the asymmetry of the distribution of phase differences between two signals; (iii) the uncorrected Amplitude Envelope Correlation (AEC) and (iv) the corrected AEC version (after performing the orthogonalisation of raw signals) (Hipp et al., 2012; Brookes et al., 2011), which provides functional coupling estimate without coherence or phase coherence; (v) the Phase Locking Value (PLV) (Lachaux et al., 1999), which detects frequency-specific transient phase locking independently from amplitude. Each of the proposed metric has different properties and capture different characteristics of the EEG signals interaction which will be discussed in this paper. We hypothesized that the choice of the metric may have a great impact in unveil subject specific pattern of functional interactions, and that advantages and disadvantages of each technique should be correctly taken into account when interpreting the corresponding results in terms of performance of a EEG based biometric system. Finally, although the aim of this study was to compare different connectivity metrics without focusing on absolute performance of the system, considering that the so called single-session approach (within-task design, where the system is tested on a single run) still represents the more important limitation of EEG based biometric systems, we replicated our study using a multi-sessions approach (between-task design, where the system is tested on multiple and different runs). Despite a within-task approach would have been adequate to test differences between the different connectivity metrics, a between-tasks approach allowed to have a more clear idea on the actual performance of the biometric system on possible real life applications.

2. Material and methods

2.1. EEG dataset

The analysis was performed using a widely used and freely available EEG dataset containing 64 channels scalp EEG recordings from 109 subjects including fourteen different runs. The full dataset was created and contributed to PhysioNet (Goldberger et al., 2000) by the developers of the BCI2000 instrumentation system. A detailed description of the original system can be found in (Schalk et al., 2004) and the access to the raw EEG recordings is possible at the following website: https://www.physionet.org/pn4/eegmmidb/. For the purpose of the present study our analysis was applied to all the fourteen different runs, using 105 out of the 109 subjects, since four of them were excluded for differences in EEG acquisition parameters. The fourteen runs are organized as follows: 1st and 2nd runs contain eyes-open and eyes close resting-state, respectively. The remaining twelve runs consist of three different repetitions of four motor tasks: (i) open and close left or right fist; (ii) imagine opening and closing left or right fist; (iii) open and close both fists or both feet and (iv) imagine opening and closing both fists or both feet.

2.2. Preprocessing

As a first step, original raw data undergo a fully automatic algorithm based on Independent Component Analysis (ICA) using ADJUST (version 1.1.1) (Mognon et al., 2011) which is optimized to detect and remove artifacts as blinks, eye movements, and generic discontinuities. Later, artifact-free EEG signals were band-pass filtered in the common frequency bands: delta (1 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 13 Hz), beta (13 - 30 Hz) and gamma (30 - 45 Hz). Finally, each single EEG recording was organized into five different epochs (without overlap) of 12 seconds which guarantee to have a correct estimate of the connectivity profiles (Fraschini et al., 2016). As a consequence, our analysis refers to one minute EEG signal for each subject and each run, so obtaining an overall of 24.5 hours of EEG recordings.

3. Connectivity metrics

From the preprocessed EEG signals, separately for each subject, each epoch and each frequency band, a connectivity matrix was computed. Each single entry of the connectivity matrix, which represents the weight of the functional interaction, was evaluated by using the following different metrics.

3.1. Correlation

The Correlation Coefficient (CC) represents the simpler method to estimate statistical relationship between two random variables and it is widely used in fMRI studies (Friston et al., 1994). However, since scalp EEG signals contain electric fields derived from common current sources, CC does not represent the optimal metric to estimate functional interactions in this context. In this study, CC was mainly applied in order to quantify the possible effect of spurious patterns of connectivity on the definition of subject specific EEG traits.

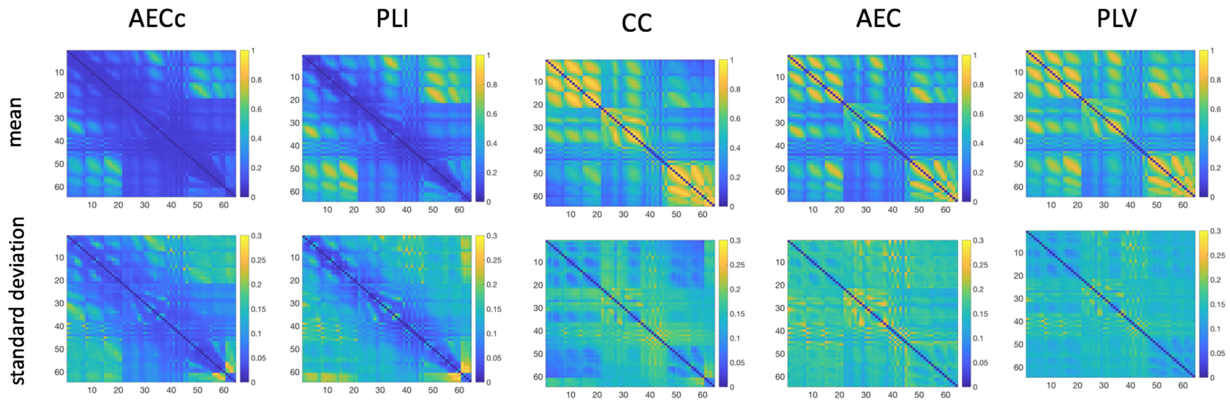

Figure 2: Connectivity patterns for each metric and corresponding between subjects variation expressed as standard deviation for eyes-closed resting-state run. Each entry represents the global average over epochs and subjects.

3.2. Phase lag index

The phase lag index (PLI) (Stam, 2014) is a technique that quantify the asymmetry of the distribution of phase differences between two signals and removes the effect of amplitude information. Furthermore, PLI is less affected by the influence of common sources and thus defines more reliable interactions between the underlying signals. The PLI is computed as the asymmetry of the distribution of instantaneous phase differences between two signals:

$$PLI = |\langle sign[\Delta\phi(t_{\mathrm{k}})]\rangle| \tag{1}$$

3.3. Amplitude Envelope Correlation

Band limited amplitude envelop correlation (AEC) (Hipp et al., 2012; Brookes et al., 2011), using Hilbert transform, was also used in this study. In particular, the envelope is obtained by measuring the magnitude of the analytic signal and successively the Pearson's correlation between envelopes is computed as a metric of functional connectivity.

3.4. Amplitude Envelope Correlation, corrected version

It is well known that signal components that pick up the same source at different sites (i.e., EEG channels) have an identical phase. In this work, to overcome this possible limitation, we used an orthogonalisation procedure performed in the spatial domain (by removing the linear regression) before to compute the AEC values. In the present paper, the corrected version of AEC is reported as AECc.

3.5. Phase Locking Value

The phase locking value (PLV), introduced by (Lachaux et al., 1999), allows to detect transient phase locking values which are independent of the signal amplitude. The PLV therefore represents the absolute value of the mean phase difference between the two signals:

$$PLV(i, j) = |\frac{1}{T}\sum e^{j[\phi k(i) - \phi k(j)]}| \tag{2}$$

4. Performance evaluation

The performance obtained by applying the different connectivity metrics have been reported in terms of Equal Error Rate (EER). The EER refers to the rate at which both acceptance error (that occurs when the system accepts an impostor) and rejection error (that occurs when the system rejects a genuine match) are equal. It represents a quick and efficient way to compare the accuracy of different systems and it is widely used in evaluating the performance of biometric fingerprints. In short, the EER is the point where false identification and false rejection rates are equal, thus the lower the EER, the better the performance of the system. As previously proposed (Fraschini et al., 2015), the system performance is based on the computation of genuine and impostor matching scores. The scores, computed separately for each frequency band, represent the Euclidean distance (d) between each pair of feature vectors. The feature vectors are represented by the individual connectivity profiles extracted from the upper (or lower) triangular (symmetrical) connectivity matrix obtained by using the different metrics. Therefore, each feature vector contains (number of channels) × (number of channels - 1) / 2 elements, where each element represents the corresponding connectivity value between a pair of EEG channels. Finally, from the matching scores, the similarity scores was computed as $1/(1 + d)$, where d represents the Euclidean distance. All these steps lead to a square (symmetrical) score matrix with a number of rows and columns equal to 7350 (14 runs × 105 subjects × 5 epochs). Finally, a 14 × 14 square matrix, containing the EER values for each combination of runs is obtained: in-diagonal values represent within-task performance; out-diagonal values represent between-tasks performance. Figure 1 shows a schematic representation of the different steps involved in the analysis.

5. Results

As a first step, in order to highlight the inherent dissimilarities between the different metrics, Figure 2 shows the global averaged (over epochs and subjects) connectivity matrices and corresponding subject's variance (expressed as standard deviation) for the eyes-closed resting-state condition. Successively, a summary of the results (in terms of EER) obtained from the whole analysis, for each frequency band and each connectivity metric separately, are summarized in Figure 3. The remaining of the results are organized into two main sub-sections. In the first sub-section (5.1), we reported the results derived from the within-task approach, the second sub-section (5.2) contains the results from the between-tasks comparison.

5.1. Within task

The results from within-task analysis, which represents the best and more trivial situation where the performance are evaluated within the same task, show the absolute higher performance in the beta band with an EER = 0.09% for the PLV connectivity metric. A graphical representation of the results is reported in Figure 3, see in-diagonal values from each single EER matrix. The other connectivity metrics performed worse, with the best EER ranging from 26.9% for AECc (beta band) to 0.57% for CC (beta band). PLI and AEC best performance were respectively equal to 3.65% (gamma band) and 4.94% (beta band). PLV and CC performed well for all the frequency bands with range from 5.37% (alpha band) to 0.09% (beta band) for PLV and from 7.03% (alpha band) to 0.57% (beta band) for CC, AECc showed the worst absolute results, with range from 41.9% (delta band) to 26.9% (beta band). For PLI, CC and PLV the results were consistent across tasks since the within task analysis that showed the lower performance were still acceptable. In details, the corresponding EER were: 8.52% for PLI (gamma band), 3.78% for CC (beta band) and 2.37% for PLV (beta band). A summary of the performance over the different within-task are included in the Table 1.

5.2. Between tasks

The results from between-tasks analysis, which represents the more realistic and challenging situation where the performance are evaluated between (all the) different tasks, show the absolute higher performance in the beta band with an EER = 7.38% for the PLV connectivity metric. Figure 3 shows the corresponding pairwise performance in the out-diagonal entries of each single EER matrix. The other connectivity metrics performed worse, with the best EER ranging from 35.03% for AECc (beta band) to 8.14% for CC (beta band). PLI and AEC best performance were respectively equal to 21.89% (beta band) and 14.23% (beta band). PLV and CC performed well for all the frequency bands with range from 15.00% (delta band) to 7.38% (beta band) for PLV and from 19.74% (delta band) to 8.14% (beta band) for CC, AECc showed the worst absolute results, with range from 46.05% (delta band) to 35.03% (beta band). A summary of the performance over all the different between-tasks are included in the Table 2.

6. Discussion

The present paper aimed to investigate and compare the impact of common metrics used to estimate functional connectivity on their capacity to detect personal distinctive fingerprints. In summary, the results of this

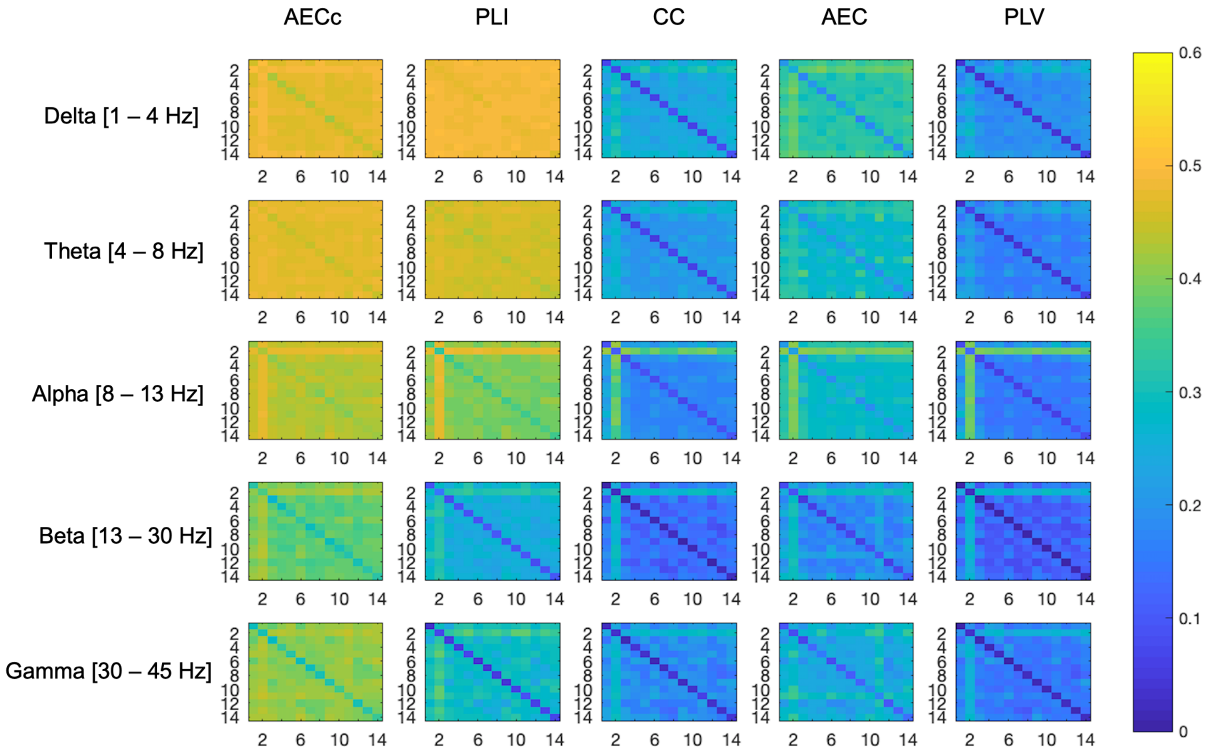

Figure 3: Results in terms of EER obtained from the whole analysis, for each frequency band (rows) and each connectivity metric (columns).

Table 1: Worst (left) and best (right) within-task performance for the different connectivity metrics expressed as EER for each frequency band. EER values lower than 10% were marked as bold.

	AECc	PLI	CC	AEC	PLV
Delta	48.29 - 41.89	48.90 - 46.06	**9.27** - **5.91**	25.30 - 15.32	**5.65** - **3.30**
Theta	46.22 - 43.33	45.25 - 42.98	**8.20** - **5.01**	23.97 - 17.54	**7.34** - **3.19**
Alpha	42.79 - 39.38	36.58 - 33.43	10.17 - **7.03**	24.78 - 18.67	12.67 - **5.37**
Beta	36.34 - 26.86	14.06 - **8.37**	**3.78** - **0.57**	10.28 - **4.94**	**2.37** - **0.09**
Gamma	36.71 - 28.64	**8.52** - **3.65**	**5.76** - **1.55**	17.90 - **7.44**	**2.90** - **0.58**

study show that, as expected, different connectivity metrics, each characterized by different mechanisms of functional interaction, define a peculiar subjective profile of connectivity. In particular, PLV and CC show excellent performance for the within-task approach, PLI and AEC show slightly lower performance which is however dependent on the frequency content. AECc, which underwent to the orthogonalization procedure to limit signal leakage, shows the worst overall performance even in the more favorable situation (single-session approach). Furthermore, despite the inherent complexity which characterize a multi-sessions approach, where the performance are assessed between different tasks, PLV and CC still show interesting (although reduced) performance with peak accuracy of 7.38% and 8.14% respectively, for the beta band. This last result represents probably the more interesting

Table 2: Worst (left) and best (right) between-tasks performance for the different connectivity metrics expressed as EER for each frequency band. EER values lower than 10% were marked as bold. In brackets EER values when between-tasks comparison including eyes-closed resting-state conditions were excluded from the analysis.

	AECc	PLI	CC	AEC	PLV
Delta	49.92 (49.48) - 46.05	49.88 (49.82) - 47.90	32.90 (28.83) - 19.74	39.82 (37.22) - 29.51	29.12 (25.99) - 15.00
Theta	48.73 - 45.80	47.11 (46.63) - 44.42	28.76 (26.98) - 17.88	36.68 - 25.31	25.90 (24.19) - 13.57
Alpha	47.84 (45.77) - 41.67	47.92 (42.86) - 37.55	41.88 (26.49) - 15.67	41.04 (33.63) - 23.60	40.24 (27.58) - 12.56
Beta	43.59 (41.78) - 35.03	34.01 (32.13) - 21.89	29.96 (19.84) - **8.14**	30.46 (28.24) - 14.23	29.09 (18.69) - **7.38**
Gamma	44.40 (44.00) - 37.86	37.81 (32.27) - 22.53	29.47 (24.30) - 12.40	34.93 (32.64) - 18.09	27.78 (22.66) - 10.29

finding of the present study, which shows the robustness of some connectivity metrics, namely PLV and CC, to detect individual fingerprints even in the more challenging experimental design. The absolute worst performance in the case of between-tasks approach, as can be visually seen from the Figure 3 (second row/column) and as reported in Table 2 in brackets, are particularly influenced by the eyes-closed resting-state task, which represents the only run where the subjects were required to close their eyes during the EEG recording. However, in our opinion, two relevant points deserve particular attention. The first important point is related to a marked association between the frequency content and the ability to discriminate among different subjects at least for the metrics which are more robust to volume conduction and signal leakage problems. Indeed, for both the experimental designs (within and between-tasks approaches) the best performance (lower EER) were obtained for the higher frequency bands (beta and gamma). It is interesting to note that this finding represents a confirmation of previously reported results using different approaches (Crobe et al., 2016; Fraschini et al., 2015). In this context, it is not possible to rule out the hypothesis that muscle artifacts, particularly evident at high frequencies (Muthukumaraswamy, 2013), may play a key role in the definition of distinctive characteristics. The second point is related to the different performance obtained using the different class of connectivity estimators. It is evident that some of connectivity metrics, namely AECc and PLI, give the lower performance even for the higher frequency bands (especially evident for the between-tasks approach). This event may be, at least in part, due to the inherent common properties of these two approaches that try to limit the signal leakage problem, which probably go to the detriment of individual characteristics regressing out subject specific features. The other way around, it should be noted that PLV is a connectivity metric that is deeply influenced by mechanisms of volume conduction, signal spread and common sources. Therefore, caution should be used when interpreting the reported results. In particular, it is still possible that the distinctive patterns of connectivity, as highlighted by PLV (and CC), may be strongly influenced by spurious connectivity values generated by the previously cited sources of noise (i.e., volume conduction, signal spread and common sources). Despite these limitations, it is surprising that even in the worst scenario, when the subjects are matched during different activities, for some connectivity metrics (i.e., CC and PLV) and specific tasks it is still possible to observe very interesting performance. Future works should investigate if the results reported so far at scalp level still hold when the EEG signals are reconstructed (by resolving the inverse problem) at source level where the effects due to spurious connections are, at least in part, attenuated (Lai et al., 2018).

7. Conclusions

Finally, this work suggests that different functional connectivity metrics have different mechanism to detect subject specific patterns of inter-channel interactions, that it is important to consider the effect of the frequency content and that spurious connectivity values may play an important role in this context.

References

Abo-Zahhad, M., Ahmed, S.M., Abbas, S.N., 2016. A new multi-level approach to eeg based human authentication using eye blinking. Pattern Recognition Letters 82, 216–225.

Armstrong, B.C., Ruiz-Blondet, M.V., Khalifian, N., Kurtz, K.J., Jin, Z., Laszlo, S., 2015. Brainprint: Assessing the uniqueness, collectability, and permanence of a novel method for erp biometrics. Neurocomputing 166, 59–67.

Barra, S., Casanova, A., Fraschini, M., Nappi, M., 2017. Fusion of physiological measures for multimodal biometric systems. Multimedia Tools and Applications 76, 4835–4847.

Brigham, K., Kumar, B.V., 2010. Subject identification from electroencephalogram (eeg) signals during imagined speech, in: Biometrics: Theory Applications and Systems (BTAS), 2010 Fourth IEEE International Conference on, IEEE. pp. 1–8.

Brookes, M.J., Hale, J.R., Zumer, J.M., Stevenson, C.M., Francis, S.T., Barnes, G.R., Owen, J.P., Morris, P.G., Nagarajan, S.S., 2011. Measuring functional connectivity using meg: methodology and comparison with fcmri. Neuroimage 56, 1082–1104.

Campisi, P., La Rocca, D., 2014. Brain waves for automatic biometric-based user recognition. IEEE transactions on information forensics and security 9, 782–800.

Crobe, A., Demuru, M., Didaci, L., Marcialis, G.L., Fraschini, M., 2016. Minimum spanning tree and k-core decomposition as measure of subject-specific eeg traits. Biomedical Physics & Engineering Express 2, 017001.

Das, R., Maiorana, E., La Rocca, D., Campisi, P., 2015. Eeg biometrics for user recognition using visually evoked potentials, in: Biometrics Special Interest Group (BIOSIG), 2015 International Conference of the, IEEE. pp. 1–8.

Del Pozo-Banos, M., Alonso, J.B., Ticay-Rivas, J.R., Travieso, C.M., 2014. Electroencephalogram subject identification: A review. Expert Systems with Applications 41, 6537–6554.

DelPozo-Banos, M., Travieso, C.M., Weidemann, C.T., Alonso, J.B., 2015. Eeg biometric identification: a thorough exploration of the time-frequency domain. Journal of neural engineering 12, 056019.

Fraschini, M., Demuru, M., Crobe, A., Marrosu, F., Stam, C.J., Hillebrand, A., 2016. The effect of epoch length on estimated eeg functional connectivity and brain network organisation. Journal of neural engineering 13, 036015.

Fraschini, M., Hillebrand, A., Demuru, M., Didaci, L., Marcialis, G.L., 2015. An eeg-based biometric system using eigenvector centrality in resting state brain networks. IEEE Signal Processing Letters 22, 666–670.

Friston, K.J., Worsley, K.J., Frackowiak, R.S., Mazziotta, J.C., Evans, A.C., 1994. Assessing the significance of focal activations using their spatial extent. Human brain mapping 1, 210–220.

Garau, M., Fraschini, M., Didaci, L., Marcialis, G.L., 2016. Experimental results on multi-modal fusion of eeg-based personal verification algorithms, in: Biometrics (ICB), 2016 International Conference on, IEEE. pp. 1–6.

Goldberger, A.L., Amaral, L.A., Glass, L., Hausdorff, J.M., Ivanov, P.C., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.K., Stanley, H.E., 2000. Physiobank, physiotoolkit, and physionet. Circulation 101, e215–e220.

Han, C., Kim, S., Yoon, H., Lee, W., Park, C., Kim, K., Park, K., 2015. Contrast between spectral and connectivity features for electroencephalography based authentication, in: World Congress on Medical Physics and Biomedical Engineering, June 7-12, 2015, Toronto, Canada, Springer. pp. 1224–1227.

Hipp, J.F., Hawellek, D.J., Corbetta, M., Siegel, M., Engel, A.K., 2012. Large-scale cortical correlation structure of spontaneous oscillatory activity. Nature neuroscience 15, 884.

Khalifa, W., Salem, A., Roushdy, M., Revett, K., 2012. A survey of eeg based user authentication schemes, in: Informatics and Systems (INFOS), 2012 8th International Conference on, IEEE. pp. BIO–55.

Kida, T., Tanaka, E., Kakigi, R., 2016. Multi-dimensional dynamics of human electromagnetic brain activity. Frontiers in human neuroscience 9, 713.

La Rocca, D., Campisi, P., Vegso, B., Cserti, P., Kozmann, G., Babiloni, F., Fallani, F.D.V., 2014. Human brain distinctiveness based on eeg spectral coherence connectivity. IEEE transactions on Biomedical Engineering 61, 2406–2412.

Lachaux, J.P., Rodriguez, E., Martinerie, J., Varela, F.J., 1999. Measuring phase synchrony in brain signals. Human brain mapping 8, 194–208.

Lai, M., Demuru, M., Hillebrand, A., Fraschini, M., 2018. A comparison between scalp-and source-reconstructed eeg networks. Scientific reports 8, 12269.

Light, G.A., Williams, L.E., Minow, F., Sprock, J., Rissling, A., Sharp, R., Swerdlow, N.R., Braff, D.L., 2010. Electroencephalography (eeg) and event-related potentials (erps) with human participants. Current protocols in neuroscience , 6–25.

Mognon, A., Jovicich, J., Bruzzone, L., Buiatti, M., 2011. Adjust: An automatic eeg artifact detector based on the joint use of spatial and temporal features. Psychophysiology 48, 229–240.

Muthukumaraswamy, S., 2013. High-frequency brain activity and muscle artifacts in meg/eeg: a review and recommendations. Frontiers in human neuroscience 7, 138.

Palaniappan, R., Mandic, D.P., 2007. Eeg based biometric framework for automatic identity verification. The Journal of VLSI Signal Processing Systems for Signal, Image, and Video Technology 49, 243–250.

Riera, A., Dunne, S., Cester, I., Ruffini, G., 2008. Starfast: A wireless wearable eeg/ecg biometric system based on the enobio sensor, in: Proceedings of the international workshop on wearable micro and nanosystems for personalised health.

Ruiz-Blondet, M.V., Jin, Z., Laszlo, S., 2016. Cerebre: A novel method for very high accuracy event-related potential biometric identification. IEEE Transactions on Information Forensics and Security 11, 1618–1629.

Schalk, G., McFarland, D.J., Hinterberger, T., Birbaumer, N., Wolpaw, J.R., 2004. Bci2000: a general-purpose brain-computer interface (bci) system. IEEE Transactions on biomedical engineering 51, 1034–1043.

Stam, C.J., 2014. Modern network science of neurological disorders. Nature Reviews Neuroscience 15, 683.

Stam, C.J., Nolte, G., Daffertshofer, A., 2007. Phase lag index: assessment of functional connectivity from multi channel eeg and meg with diminished bias from common sources. Human brain mapping 28, 1178–1193.

Yang, S., Deravi, F., Hoque, S., 2018. Task sensitivity in eeg biometric recognition. Pattern Analysis and Applications 21, 105–117.