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It's a Question of Methods: Computational Factors Influencing the Frontal Asymmetry in Measuring the Emotional Valence

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Abstract— **The prefrontal asymmetry (FA) in the alpha band is a well-known physiological correlate of the emotional valence. Several methods for assessing the FA have been proposed in literature, but no studies have compared their effectiveness in a comprehensive way. In this study we first investigated whether the association between FA and valence depends on the computational methods and then, we identified the best one, namely the one giving the highest correlation with the self-reports. The investigated factors were the presence of a normalization factor, the computation in time or frequency domain and the cluster of electrodes used. All the analyses were implemented on the validated DEAP dataset. We found that the number and position of the electrodes do not influence the FA, in contrast with both the power computation method and the normalization. By using a spectrogram-based approach and by adding a normalization factor, a correlation of 0.36 between the FA and the self-reported valence was obtained.**

I. INTRODUCTION

The automatic measurement of emotions, using e.g. low cost and wearable devices [1], is a key topic in several modern disciplines, such as Affective Computing [2], Brain-Computer Interfaces [3], Neuroergonomics [4] and Consumer Behavior [5].

A great contribution in the emotion measurement is given by validated datasets. They contain emotional stimuli alongside with both the corresponding subjective evaluations and objective bioelectrical responses. The emotional datasets are typically used by researchers as a benchmark to train and test automatic emotion recognition systems [6].

According to the Dimensional Theory, emotions can be identified by two dimensions: the arousal, ranging from boring to exciting, and the valence, ranging from pleasure to displeasure [7]. They both underline various physiological correlates. The valence, in particular, can be assessed from the neural activity of the prefrontal cortex [8].

Compared with the right one, a greater activity of left prefrontal cortex correlates with an approach response to a stimulus. Conversely, compared with the left one, a greater activity of the right prefrontal cortex is correlated with a withdrawal. This difference in the prefrontal cortex activity is called "prefrontal asymmetry", or simply "frontal asymmetry" (hereinafter, FA) [9].

The approach-withdrawal response [9] correlates with the valence for most of the emotions, except for anger, where a negative valence is associated with an approach response [10]. It is worth noting that the extent to which FA can be considered as moderator or mediator of emotions is still debated [11] and its robustness in measuring the emotional valence have been sometimes questioned [10]. Nevertheless, the FA is still generally considered as "the index" of emotional valence [8].

The FA is computed as the difference in the alpha power between the right and the left hemispheres. As shown in Sect. II, FA can be computed in various ways, depending on the combination of the following 3 factors:

- Cluster - number and position of the electrodes;
- Processing - domain for the processing (time or time-frequency);
- Normalization - presence or absence of a normalization term.

To the best of our knowledge, no studies have compared these factors in a comprehensive way.

In this study we investigated the different computational approaches to FA, correlating their results with the emotional assessment. Then we identified the best one, namely the one giving the highest correlation with the self-reported valence.

All the computational approaches were implemented on the validated DEAP dataset [12] considering, in particular, the electroencephalographic data and the scores from the self-reported valence.

II. STATE OF THE ART

Among all the existing neuroimaging tools, the electroencephalogram (EEG) is the most widely used because of its low cost, noninvasivity and high temporal resolution [13].

When measured with the EEG, the FA is defined in terms of alpha asymmetry, since the electrical power in alpha band ($8-12\ Hz$) is inversely related to the neural activity: a greater left-over-right prefrontal activity corresponds to a greater right-over-left alpha prefrontal asymmetry and vice-versa [11].

FA can be computed as a score, obtained in the frequency domain, or as a time-varying signal, obtained in either the time or time-frequency domain. As shown in Sect. II-C, the two definitions are at least approximately equivalent, so long as comparing the FA score with the temporal average of the FA signal.

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A. FA score

The FA score (hereinafter, A) follows the original definition of frontal alpha asymmetry [14]. It is obtained by calculating the Welch's periodogram of the signals recorded from 2 homologous prefrontal electrodes, one located on the right and one on the left side. Then, the corresponding Power Spectral Densities (PSDs) are integrated over the alpha band, in order to obtain right (R) and left (L) average powers. Finally, the average powers are subtracted, as [15]:

$$A = R - L \tag{1}$$

Typical electrode locations include the mid-frontal (F4, F3) and the front-lateral (F6, F5 or F8, F7) regions, while the frontal-pole (FP2, FP1) is less commonly reported [11].

In order to obtain a more robust estimate, instead of two homologous electrodes, two clusters of electrodes positioned on homologous locations of the prefrontal cortex can be considered [16]. Right (C_R) and left (C_L) cluster average powers are calculated by averaging the average powers within each cluster:

$$\begin{aligned} C_R &= \frac{1}{N_R}\sum_{i=1}^{N_R} R_i \\ C_L &= \frac{1}{N_L}\sum_{i=1}^{N_L} L_i \end{aligned} \tag{2}$$

N_R and N_L are the number of electrodes in the right and left cluster, respectively. R_i and L_i are the $i-$th average powers in the left and right cluster, respectively.

A is then obtained by the difference between C_R and C_L [16]:

$$A = C_R - C_L \tag{3}$$

As a step before the subtraction, values are often log-transformed, in order to mitigate the skewness of the power values [17].

B. FA signal

An alternative representation of the FA is a time-varying signal, $A[n]$. It is obtained by subtracting, as in (1), two instant alpha powers, calculated in the time domain by squaring the alpha-filtered signal. The signals come from 2 homologous prefrontal electrodes: 1 on the right, $R[n]$, and 1 on the left, $L[n]$ [18].

Similarly to A, $A[n]$ can be computed considering more than 2 electrodes. The instant powers of multiple electrodes are averaged together into a right and a left cluster instant power, $C_R[n]$ and $C_L[n]$, computed as in (2). Then, $A[n]$ is computed as in (3) [19].

Typical clusters include (Fp2, AF6, AF4, F4) and (Fp1, AF7, AF3, F5) [20]; (AF6, AF8) and (AF5, AF7) [19]; (Fp2, AF4, AF6, AF8) and (Fp1, AF3, AF5, AF7) [21].

Instead of filtering and squaring a raw signal, the instant powers $R[n]$ and $L[n]$ can be calculated in the time-frequency domain by integrating over the alpha band the spectrograms of the raw signals from 2 homologous electrodes. When multiple electrodes are considered, the cluster instant powers are still computed by averaging the instant powers within each cluster [22].

As with A, $R[n]$ and $L[n]$ can be log-normalized before the subtraction [22].

C. Score-signal equivalence

The temporal average of $A[n]$, obtained following the spectrogram method, is equivalent to A, obtained by the Welch's periodogram, either considering 2 homologous electrodes or, due to the linearity of the average operation, 2 clusters of homologous electrodes.

Likewise, the temporal average of $A[n]$, obtained by the filtering method, is almost equivalent (implicitly assuming as negligible the power in the filter's transition band) to A, obtained by the Welch's periodogram, either considering 2 homologous electrodes or, due to the linearity of the average operation, 2 clusters of homologous electrodes.

D. Normalization

In order to mitigate the inter-individual differences in EEG powers, A is normalized by adding the quantity $(R + L)$ as denominator to (1) [23]. This is mostly applied to not log-transformed data, giving almost equivalent results to the subtraction of the corresponding log-transformed data [15]. It has to be noted that this normalization has been also applied to log-transformed data [24]: rather than a normalization, it corresponds to the nonlinear transformation $\log_{RL}(R/L)$.

III. METHODS

A. The DEAP Dataset

The DEAP dataset [12] contains the bioelectrical data and the self-reports of 32 healthy subjects acquired while watching 40 different music video clips.

An initial pool of 120 music videos, spanning uniformly the 4 quadrants of the Russel's circumplex model [25], was created. Half were selected semi-automatically, using tags from a music enthusiast website and half manually by the DEAP's authors. The final set of 40 videos was selected from the initial pool using a web-based interface: users rated the videos based on the perceived valence, arousal and dominance. For each quadrant of Russell's circumplex model the 10 videos closest to the extreme corner were chosen. For each video, the 60-second-long segment with the highest emotional highlight score was extracted.

Bioelectrical data include EEG, skin-conductance, respiration, and others. The EEG was recorded from 32 channels, 12 of which on the frontal and pre-frontal regions: 6 on the left (FP1, AF3, F3, F7, FC5, FC1) and 6 on the right side (FP2, AF4, F4, F8, FC6, FC2). The sample rate was 512 Hz.

The self-reports include the subjective ratings of each video clips, expressed in terms of valence, arousal, dominance and liking - all assessed trough the Self-Assessment Manikin [26].

B. Processing

DEAP dataset is publicity available on a dedicate web site (`http://www.eecs.qmul.ac.uk/mmv/datasets/deap/`) and contains both the raw and processed bioelectrical data. The EEG was processed with the following steps: common average reference, down-sample to 128 Hz, band-pass filter ($4.0-45.0\ Hz$) and artifact removal using the Independent Component Analysis (ICA). In the present work we used the processed EEG data.

Considering only the prefrontal electrodes (6 in each side), $2^6 - 1 = 63$ different clusters can be identified. For each cluster, we computed the $A[n]$ using the filter and spectrogram methods described in Sect. II. The filter method was based on a zero-phased band-pass Butterworth filter (4th order) between 8 and 12 Hz. The spectrogram was based on a short-time Fourier transform (STFT) using a 1 s long Hamming window with 50% of overlapping.

In both cases we applied the log-transformation and computed the normalized and not normalized FA. Finally, A was computed by temporal averaging $A[n]$.

For each subject l, an FA vector $\mathbf{A}_l$ was created by concatenating the A of each stimulus. Similarly, the valence vector $\mathbf{v}_l$ was created by concatenating the corresponding valence assessments.

C. Statistical Analysis

The correlation between the FA vector and the self-reported valence was computed by means of the Spearman's correlation coefficient ρ:

$$r_{l,m,c,n} = \rho(\mathbf{v}_l, \mathbf{A}_{l,m,c,n}) \tag{4}$$

where $\mathbf{v}_l = (v_l(1), ..., v_l(N))^T$ is the valence vector and $\mathbf{A}_{l,m,c,n} = (A_{l,m,s,n}(1), ..., A_{l,m,s,n}(N))^T$ is the FA vector. The indices $l = \{1, ..., N_l\}$, $m = \{1, ..., N_m\}$, $c = \{1, ..., N_c\}$ and $n = \{1, ..., N_n\}$ are, respectively, the participant, method, cluster and normalization indices.

The set of the 8064 correlation coefficients ($N_l = 32$, $N_m = 2$, $N_c = 63$, $N_n = 2$) described in (4) formed the raw correlation table. Only the subset of significant (i.e. $p \leq 0.1$, not corrected for multiple comparisons) elements were considered for the analyses.

A total of 2589 significant correlations were analyzed using a 3-way ANOVAs, considering as factors: the method (2 levels: Spectrogram, S and filtering, F), the normalization (2 levels: normalized, N and un-normalized, U) and the cluster (63 levels). The statistical analyses were performed using JASP v.0.14 [27].

IV. Results

Significant main effects for method ($F(1, 2337) = 215.045$, $p < 0.001$) and normalization ($F(1, 2337) = 64.520$, $p < 0.001$), as well as a significant interaction effect for method × normalization ($F(1, 2337) = 149.904$, $p < 0.001$) were found.

The following results are reported as mean (M) and standard error (SE). Post-hoc comparisons (Bonferroni corrected) confirmed that F ($M = 0.018$, $SE = 0.010$) was associated to a lower correlation than S ($M = 0.220$, $SE = 0.009$). N ($M = 0.174$, $SE = 0.010$) was associated to higher correlation than U ($M = 0.063$, $SE = 0.010$). Finally, in Table I the results for the method × normalization interaction are reported. As visible also in Fig.1, the combination of S and N gives the best computational method for FA, corresponding to a correlation of 0.357.

TABLE I
MARGINAL MEANS - METHOD × NORMALIZATION

Method	Norm.	Mean	95% CI Lower	95% CI Upper	SE
F	N	-0.010	-0.039	0.020	0.015
S		0.357	0.334	0.381	0.012
F	U	0.045	0.017	0.073	0.014
S		0.082	0.055	0.108	0.013

Norm = Normalization; Mean = Marginal Mean.

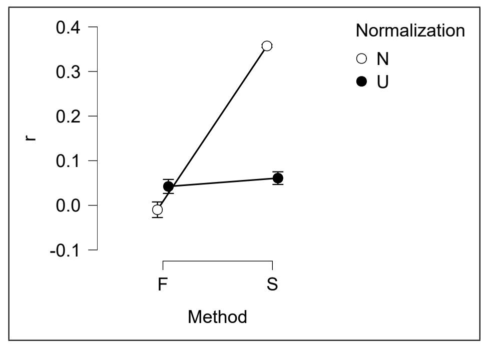

Fig. 1. Correlation (r) between the valence and the asymmetry index computed for the two methods (F, S) and with/without normalization (N, U).

V. Conclusion

In this paper we investigated the reliability of the FA in measuring the emotional valence with respect to 3 factors: the cluster of electrodes, the method (spectrogram or filtering) and the normalization. The aim was to select the best approach to be used in emotions assessment. By using the validated DEAP dataset [12], we tested the performances of different computational methods, obtained by combining the above-mentioned factors. The figure of merit was the correlation between the FA and the self-reported valence.

We did not find any significant effect for the cluster. However, we found significant effects for both the method and the normalization.

The non-significant effect for the cluster suggests that the FA could be effectively computed using even only 2 prefrontal electrodes. Even if the FA is not correlated to the number of used electrodes, a sufficient (e.g. 20 or more) number of channels is still required for an effective ICA denoising [28] and, consequently, a cleaner EEG signal for the FA computation.

The found positive effect of the normalization is in line with the literature, where an effect in reducing inter-individual differences has been reported [23]. In comparison to the filter, the better performance of the spectrogram could be due to the not-ideal implemented filter, as noted in section II-C. Indeed, the non-infinite steep filter adds to both R and L spectral power outside the alpha band that could exhibit a different asymmetric pattern related to the emotional valence. This hypothesis should be further verified.

Overall, the found correlations are low (< 0.4), confirming that the prefrontal asymmetry is not always a robust measure of the emotional valence [10]. The results, however, are in line with the literature that reports low and sometimes non-significant values. In [29], the authors reported a maximum correlation value of 0.16, while in [30] the authors found a maximum correlation value of 0.19. In [31], the maximum beta coefficient for the linear regression between frontal asymmetry and valence was of 0.3 and in [32] the correlation was not significant.

In conclusion, after the assessment of the factors influencing the FA, we suggest as the best technique the use of the normalization term in the $FA[n]$, computed by means of the spectrogram method.

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