Prediction of Human Empathy based on EEG Cortical Asymmetry

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Abstract—Humans constantly interact with digital devices that disregard their feelings. However, the synergy between human and technology can be strengthened if the technology is able to distinguish and react to human emotions. Models that rely on unconscious indications of human emotions, such as (neuro)physiological signals, hold promise in personalization of feedback and adaptation of the interaction. The current study elaborated on adopting a predictive approach in studying human emotional processing based on brain activity. More specifically, we investigated the proposition of predicting self-reported human empathy based on EEG cortical asymmetry in different areas of the brain. Different types of predictive models i.e. multiple linear regression analyses as well as binary classifications were evaluated. Results showed that lateralization of brain oscillations at specific frequency bands is an important predictor of self-reported empathy scores. Additionally, prominent classification performance was found during resting-state which suggests that emotional stimulation is not required for accurate prediction of empathy -as a personality trait- based on EEG data. Our findings not only contribute to the general understanding of the mechanisms of empathy, but also facilitate a better grasp on the advantages of applying a predictive approach compared to hypothesis-driven studies in neuropsychological research. More importantly, our results could be employed in the development of brain-computer interfaces that assist people with difficulties in expressing or recognizing emotions.

Index Terms—affective computing, empathy, brain activity, EEG asymmetry, classification, brain-computer interface

I. INTRODUCTION

One of the challenges in the field of human-technology interaction that has long received attention is to endow a machine with the ability to understand and react to a user’s emotions. As many studies have focused on the analysis of behaviour modalities [1], recently, research is leaning toward emotion recognition based on (neuro)physiological data [2].

Emotion recognition based on neuroimaging approaches can be used for improvement of interaction between human and technology. Artificial agents that are able to predict human affective states would give rise to virtual diagnosing of social behaviour disorders while assisting these individuals on how to deal with their condition. For instance, virtual coaches can adapt their behaviour to the personality of the user, e.g. by giving verbal encouragement [3], or assist people with difficulties to express or recognize emotions [4], [5], or boost learning through recognition of boredom and frustration [6].

An important aspect of emotional regulation is empathy. Empathy is the ability to vicariously experience and understand the affect of other people and is fundamental to successful socio-cognitive functioning [7]. Past research has tried to understand the neurophysiological basis of empathy by evaluating brain activation in different areas of the brain as measured by EEG. A few studies have found a prominent role for frontal cortical asymmetry, which is the relative difference in activation between the hemispheres, in mediating empathy-related behaviors [8], [9]. These studies suggest that a relatively stronger right frontal activation is associated with empathic responses to others’ suffering. This is in line with the valence hypothesis [10], which states that the left hemisphere is specialized for processing of positive emotions and the right hemisphere is specialized for processing of negative emotions.

However, there are also inconsistencies and limitations in these reports. Whereas some studies found empathy-related asymmetry changes in low-frequency bands such as theta and delta [11], the rest reported main effects in alpha [12], [13] and high-frequency bands, such as beta and gamma [14]. Additionally, in most reports, empathy was evaluated as a state measure in response to emotional stimulation, rather than a personality trait [15], [16]. More importantly, despite the fact that previous research found an association between cortical asymmetry and human empathy, it is not clear whether it is possible to predict human empathy based on the same EEG components. Most of the existing research on EEG correlates of personality traits were conducted in a hypothesis-driven way, without giving any serious consideration to a predictive approach. Those research that attempted prediction of personality traits and emotional responding did not reach consistent conclusions; some reported a successful analysis [17], while others failed [18].

Therefore, based on the identified gap in the literature, we took a predictive approach in this study in order to estimate empathy both as a state response as well as a personality trait.
In this approach, ‘success’ is measured not by the size of a theoretically privileged regression coefficient or a model fit statistic, but instead by the average difference between unobserved data (i.e., ‘out-of-sample’ data that were not used to fit the model) and the model’s predictions for those data [19]. Thus the goal of the current study is twofold; (1) it attempts to push forward the usage of EEG analysis in the prediction and interpretation of human emotional processing, and (2) it aims to contribute to the predictive approach in neurophysiological research by applying machine learning algorithms to accommodate for the complexity of the recorded data and to guarantee a higher degree of generalizability.

II. Method

A. Data

The data was collected by a team of researchers led by the second author [16], [20]. Fifty-two participants watched an emotional 360° virtual reality (VR) video of a young African girl, who was being abused as a domestic slave (Fig. 1). EEG signals were collected from the frontal, central and occipital areas of the brain (9 electrodes: F3, Fz, F4, C3, Cz, C4, P3, POz and P4) before, during and after the stimulus. This resulted in three data segments: Pre-video segment, Video segment and Post-video segment. The EEG signals were bandpass filtered between 0.5 and 50 Hz. For every subject, an array of the mean EEG log powers was computed for five frequency bands: delta (0.5-3.9 Hz), theta (4-7.9 Hz), alpha (8-12.9 Hz), beta (13-27.9 Hz), and gamma (28-50 Hz), in every electrode and every segment. Asymmetry powers were obtained by subtracting the powers of the left hemisphere from the powers of the right hemisphere (i.e. F4–F3, C4–C3, and P4–P3). A positive asymmetry value equaled stronger activation in the right hemisphere compared to the left hemisphere. Data from three participants with influential asymmetry values (Cook’s distance larger than 3 times the mean) were excluded from further analysis.

The Toronto empathy questionnaire [21] was used to quantify the level of empathy. This self-reported questionnaire assesses behavioral, emotional, cognitive, and physiological aspects of empathy in individuals in broad spectrum. Subjects responded to questions on a 7-point Likert-scale. The possible range of self-reported empathy scores was 0 to 96. The obtained self-reported empathy scores in the current study ranged between 49 to 86. The empathy questionnaire was administered before the experiment [16].

B. Feature selection

In total, there were 15 features extracted from the EEG data (i.e. asymmetry values of five frequency bands in three brain regions) in each segment. Several feature selection methods were implemented to create a subset of best performing features. First, Linear Model Feature Ranking was implemented. This method uses three different Scikit-Learn linear models (Linear, Lasso and Ridge Regression) to create feature importance rankings. Second, Recursive Feature Elimination (RFE) was used. This method elicits rankings, ordering the features from salient to non-salient and then excludes the worst-performing features. Third, Random Forest Feature ranking was applied, using the Random Forest’s attribute ‘feature importances’ to calculate and ultimately rank the feature importance. To combine the methods, they were all integrated into one matrix, and were used to create factor plots.

C. Multiple Linear Regression (MLR)

As self-reported empathy scores were continuous data, a multiple linear regression analysis was used to look into the possibilities of predicting continuous data. Two different models were compared for each segment: 1) a model with all fifteen features; 2) a model with a subset of five features selected by the earlier described feature selection methods, combined with k-fold cross-validation (k=5). For evaluation, Mean Squared Error (MSE), Mean Absolute Error (MAE) and p-value are reported. A significant p-value (<0.05) of a predictor in a model indicates that the predictor is an effective addition to the model; the changes in the predictor’s value are proportional to changes in the response variable.

D. Binary Classification

Discretization of continuous features reduces the impact of small fluctuations in the data on the model by splitting the data into bins, and has frequently been used in studies classifying personality traits [18], [22]. Using a median split, the self-reported empathy scores were divided into two classes: ‘high’ vs. ‘low’ empathy groups. For classification, three models i.e. a Logistic Regression (LR), a Support Vector Machine (SVM), and a Decision Tree (DT) were implemented, as these are suitable for small datasets. A selection of five best performing features was used, combined with leave-one-out cross-validation. For evaluation of the models, the F1-score was used. A high F1-score means that the model produces few false positives and few false negatives.

III. Results

A. Multiple Linear Regression

When using the model with all fifteen features, a significant regression equation (ρ = 0.045) was found for the Post-video segment (see Table I). When using MLR with a selection of
best performing five features, the model significantly predicted the empathy scores in the Pre-video segment \((p = 0.046)\) i.e. before exposure to an empathy-inducing video stimulus. Moreover, when considering the contribution of selected features to the prediction (see Table II), the results indicated a significant main effect for frontal alpha asymmetry in the Pre-video segment \((p = 0.006)\) and frontal gamma asymmetry in the Post-video segment \((p = 0.010)\).

**TABLE I**

**MULTIPLE LINEAR REGRESSION MODELS PREDICTING CONTINUOUS SELF-REPORTED EMPATHY SCORES, FOR PRE-VIDEO, VIDEO, AND POST-VIDEO SEGMENTS, WITH 15 AND 5 FEATURES.**

| Segment | MSE | MAE | \(p\) |
|---------|-----|-----|-------|
| 15 features |       |     |       |
| Pre     | 51.749 | 6.735 | 0.583 |
| Video   | 122.332 | 9.206 | 0.976 |
| Post    | 150.556 | 10.231 | 0.045 |
| 5 features |       |     |       |
| Pre     | 78.850 | 8.740 | 0.046 |
| Video   | 77.876 | 7.344 | 0.407 |
| Post    | 62.102 | 6.875 | 0.057 |

**TABLE II**

**MULTIPLE LINEAR REGRESSION MODELS FOR THE PRE-VIDEO, VIDEO AND POST-VIDEO SEGMENTS AFTER FEATURE SELECTION.**

| Feature   | \(\text{coef}\) | \(t\) | \(p\) |
|-----------|-----------------|------|------|
| Pre       |                  |      |      |
| central delta | 0.315 | 1.690 | 0.051 |
| parietal delta | 3.633 | 1.040 | 0.115 |
| frontal theta | 1.479 | 0.889 | 0.384 |
| frontal alpha | -0.748 | -3.021 | 0.008 |
| central gamma | 0.455 | 0.766 | 0.452 |
| Video      |                  |      |      |
| frontal delta | 4.430 | 1.662 | 0.111 |
| parietal delta | -6.252 | -1.524 | 0.142 |
| frontal theta | -4.540 | -1.941 | 0.066 |
| parietal theta | 5.942 | 1.316 | 0.202 |
| parietal gamma | 2.899 | 0.630 | 0.536 |
| Post       |                  |      |      |
| frontal delta | 1.521 | 0.965 | 0.345 |
| frontal theta | -2.354 | -0.868 | 0.395 |
| central alpha | 1.233 | 0.463 | 0.648 |
| frontal alpha | -6.909 | -1.750 | 0.095 |
| frontal gamma | 2.414 | 2.833 | 0.010 |

**B. Binary Classification**

For binary classification, the three LR, SVM and DT models were trained only with the five best performing features (see Table III). The highest performance scores were found for the SVM classifier during the Pre-video segment (F1-score = 0.743), and during the Post-video segment (F1-score = 0.676).

**TABLE III**

**BINARY CLASSIFICATION METRICS, FOR PRE-VIDEO, VIDEO, AND POST-VIDEO SEGMENTS RESPECTIVELY, USING A LOGISTIC REGRESSION (LR), SUPPORT VECTOR MACHINE (SVM) AND DECISION TREE (DT).**

| Model          | Accuracy | Precision | Recall | F1    |
|----------------|----------|-----------|--------|-------|
| Pre LR         | 0.571    | 0.571     | 0.571  | 0.571 |
| Pre SVM        | 0.742    | 0.743     | 0.743  | 0.743 |
| Pre DT         | 0.657    | 0.658     | 0.657  | 0.655 |
| Video LR       | 0.500    | 0.500     | 0.500  | 0.496 |
| Video SVM      | 0.529    | 0.545     | 0.529  | 0.485 |
| Video DT       | 0.618    | 0.621     | 0.618  | 0.615 |
| Post LR        | 0.617    | 0.621     | 0.618  | 0.615 |
| Post SVM       | 0.676    | 0.677     | 0.676  | 0.676 |
| Post DT        | 0.647    | 0.656     | 0.647  | 0.642 |

**IV. Discussion**

The aim of this study was to examine the prospect of applying a predictive approach in studying the association between cortical asymmetry and self-reported empathy. Based on previous literature [11], [12], [16], the expectation was that it would be possible to predict human empathy using EEG asymmetry values, obtained in five frequency bands from different regions of the brain. Several methods were implemented in order to study this hypothesis including prediction of a continuous empathy score as well as a binary classification of empathy groups. Moreover, the study was interested in whether the prediction power of the models would be different when they were trained using EEG features of three different time segments; the baseline resting-state, during and after participants were exposed to an empathy-inducing video stimulus.

Based on the MLR analysis, a prominent role of frontal alpha asymmetry was found for the models in the Pre-video and Post-video segments. This is consistent with previous literature [8], [9], [12], [23], [24] in which frontal alpha asymmetry was identified as a predictor and mediator of emotional disposition and affective processing. In addition, when the model was trained with Post-video EEG data, significant main effects were found for cortical asymmetry in high-frequency bands, i.e. gamma of the frontal cortex. This is in line with the previously reported role of high-frequency bands in providing discriminative information for emotion recognition [14] as well as emotional arousal in high vs. low empathy groups [15]. None of the models could predict empathy levels in the Video segment. These results propose that empathy as a personality trait can be best predicted based on EEG cortical asymmetry in the absence of emotional stimulation. Future research should consider asymmetry changes from resting-state to the stimulus phase in order to examine the effect of affective stimulus on trait-related EEG features.

Our binary classification using SVM model outperformed that of previous neurofeedback research [25]. Even though acceptable performance was obtained in our classification of empathy groups, the large prediction errors in the regression analysis showed the inability of these models to predict continuous empathy values. This can perhaps be explained by the narrow range of the target variable and the small size of our dataset. Future work should attempt to replicate this study with more EEG data and from a broader range of participants that have been screened for their empathy scores prior to the experiment. Moreover, future studies should consider the potential influence of gender on the relationship between cortical asymmetry and empathy. Previous literature has found that women in general show greater right-dominant frontal alpha asymmetry than men [26].

Contrary to the results of a previous study, in which machine learning models failed to predict personality traits [18], our classifier showed an acceptable performance in prediction of
trait empathy. An explanation could be the large individual differences that exist in spectral power values even at the baseline. Differential asymmetry compares each person to himself and therefore entails a smaller variance. Another reason could be that the mentioned study looked at Big Five personality traits as response variables. Although past psychological studies have shown weak relationships between empathy and Big Five dimensions [27], the two are not necessarily the same.

Finally, in the present study, a specific operational definition of empathy was used, by means of the Toronto empathy questionnaire. Self-reported empathy evaluation is usually weak in detecting subtle individual differences [15]. Therefore, other methods for assessment of the complex construct of human empathy might reveal different results and should be taken into consideration in future research.

In sum, the possibility of observing and predicting human empathy on the basis of neural activity introduces a new method for emotion recognition and personality profiling. This approach can be used in providing support to individuals who struggle with social behavioural disorder by fully adapting to their condition as well as in the enhancement of human-technology interaction, where artificial agents can understand human affective states and personalize the interaction [4].

V. CONCLUSION

This study elaborated on adopting a predictive approach in identifying neurophysiological bases of human empathy. Both regression and classification algorithms were employed to predict empathy levels of humans based on EEG asymmetry powers. Promising results were found in the binary classification of ‘high’ vs. ‘low’ empathy groups, particularly in the resting-state measurements i.e. in the absence of emotional stimuli. Also a significant contribution was found for frontal alpha asymmetry in predicting empathy as a personality trait. Our results hold promise for development of future brain-computer interfaces that predict a user’s personality traits and emotional responses in order to improve the quality of interaction during technology usage.

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