Detecting Personality Traits Using Inter-Hemispheric Asynchrony of the Brainwaves

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***Abstract*—Affective personality traits have been associated with a risk of developing mental and cognitive disorders and can be informative for early detection and management of such disorders. However, conventional personality trait detection is often biased and unreliable, as it depends on the honesty of the subjects when filling out the lengthy questionnaires. In this paper, we propose a method for objective detection of personality traits using physiological signals. Subjects are shown affective images and videos to evoke a range of emotions. The electrical activity of the brain is captured using EEG during this process and the multi-channel EEG data is processed to compute the inter-hemispheric asynchrony of the brainwaves. The most discriminative features are selected and then used to build a machine learning classifier, which is trained to predict 16 personality traits. Our results show high predictive accuracy for both image and video stimuli individually, and an improvement when the two stimuli are combined, achieving a 95.49% accuracy. Most of the selected discriminative features were found to be extracted from the alpha frequency band. Our work shows that personality traits can be accurately detected with EEG data, suggesting possible use in practical applications for early detection of mental and cognitive disorders.**

I. Introduction

Personality traits can be defined as “persisting underlying tendencies to behave in particular ways in particular situations” [1]. Personality is an area in psychology but there exist strong links between personality traits and mental health. In particular, personality models differentiate between affective, cognitive, and behavioral personality traits [2], and associations between affective traits and mental and cognitive disorders were discovered and studied in depth [3, 4].

Project Talent [5] is a comprehensive longitudinal study that involved more than 440,000 high school students in the US. Using a sample of 82,232 participants, the study showed that adolescent personality traits could be a risk factor for dementia [6]. Another study under the same project uncovered links between personality traits and mortality risk [7]. In addition, other studies showed an association between personality traits and risk of Parkinson’s disease [8], and adherence to medication in individuals with chronic disease [9]. Hence, personality traits information can help clinicians for early detection of diseases and preventative activities [10].

However, such preventative healthcare requires reliable personality data. Personality traits are traditionally measured using personality tests, such as the commonly used personality inventories [11-15]. These are lengthy self-reported questionnaires assessing various aspects of personality that are filled out by the subjects. The outcomes of the personality tests depend on how well the subjects understand the questions and on their honesty and motivation in answering the questions [16]. Therefore, personality traits detected using conventional methods can be highly subjective, biased, and unreliable.

In this work, we propose and evaluate a method for *objective detection of personality traits using physiological signals* [17]. Subjects are shown a range of image and video stimuli designed to evoke emotional responses revealing personality traits from three well-known models: Dark Triad (D3) [18], reinforcement sensitivity or BIS/BAS [19], and HEXACO [20]. Electroencephalogram (EEG) is used to capture the brain responses while the subjects are shown the stimuli. The EEG signals are analyzed and used to build machine learning classifiers. Once trained, these classifiers can be used to predict personality traits of new subjects.

In particular, in this work we explore the relationships between personality traits and the correlation of the spectral energy in the brainwaves of the two hemispheres, referred to as *inter-hemispheric asynchrony*, which were shown to be useful in sleep research [21]. Our results suggest that the proposed method could be useful in detecting personality traits. Brain asynchrony in the alpha frequency band showed the strongest correlation with the detected personality traits.

The rest of the paper is organized as follows. In Section II we outline the method used in this work, including the dataset, EEG feature extraction, and the machine learning classifiers. The experimental results are presented in Section III and the discussion and conclusions in Section IV.

II. Methods

An overview of the proposed method is shown in Fig. 1 and specifics are described in detail in the following subsections. The subjects, whose personality was being predicted, were shown affective image and video stimuli and their brain activity was measured using EEG. The EEG signals were processed, analyzed, and classified in order to evaluate the prediction accuracy of the personality traits. The actual personality traits of the subjects, used as the target

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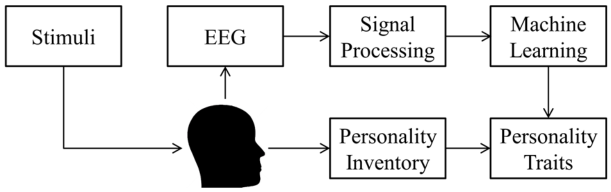

Figure 1. Overview of the proposed method [17].

class to build the machine learning classifiers, were established using traditional personality inventories.

A. Dataset

The dataset used in this work contains a total of 18 subjects: 15 subjects aged 18 to 30 and 3 subjects older than 30. All the subjects were staff or students of a research organization. Their personality traits (listed in Table I) were established using the following personality inventories: (i) Levenson's self-report psychopathy inventory, which assesses Primary and Secondary Psychopathy [11], (ii) narcissistic personality inventory (NPI-16) that assesses Narcissism [12], (iii) MACH-IV that measures Machiavellianism, including Tactics, Morality, and Views [13], (iv) BIS/BAS inventory that assesses BIS, BIS Drive, BAS Fun Seeking, and BAS Reward Responsiveness [14], and (v) the HEXACO traits (Agreeableness, Conscientiousness, Extraversion, Honesty, Resiliency, and Openness) were assessed using a 25-item inventory [15].

Data was collected in a controlled laboratory setting and the experimental procedures involving human subjects were approved by the institutional ethics review board. Subjects were shown a set of 50 images from the International Affective Picture System (IAPS) dataset [22]. The 50 IAPS images were split into 10 blocks across five categories: strong positive emotions, mildly positive emotions, mildly negative emotions, strongly negative emotions, and neutral. Video stimuli were taken from the English version of the FilmStim dataset [23] to represent seven emotion types: fear, tenderness, anger, neutral, sadness, amusement, and disgust. Each block was preceded by a cool-down period used as a baseline.

The electrical activity of the brain, while the subjects were exposed to the affective stimuli, was captured using the Emotiv 14-channel wireless EEG headset. The EEG signals were recorded at a sampling frequency of 128 Hz. In an ideal case, the EEG signals would have been used to predict the numeric values of the subject's personality traits. However, data from 18 subjects would not allow accurate predictions and generalizable results. Hence, the personality trait data was discretized into three equal-sized groups (low, medium, and high) for each trait, based on the scores obtained from the personality inventories, as described in [17]. An overview of the different personality traits and the observed subjects' score ranges within the three groups is given in Table I.

TABLE I. PERSONALITY SCORES (THE 'RANGE' COLUMN SHOWS THEORETICAL TRAIT RANGES WHILE 'LOW', 'MEDIUM', AND 'HIGH' REFLECT OUR STUDY OBSERVATIONS)

Trait	Range	Low	Med	High
Primary Psychopathy	[16,64]	[21,28]	[28,32]	[33,40]
Secondary Psychopathy	[10,40]	[17,19]	[20,21]	[22,25]
Tactics	[9,45]	[19,20]	[20,26]	[27,32]
Views	[9,45]	[17,22]	[22,25]	[25,32]
Morality	[2,10]	[2,5]	[5,6]	[6,8]
Narcissism	[0,100]	[0,13]	[18,44]	[44,82]
BIS	[7,28]	[15,18]	[19,21]	[21,26]
BAS Drive	[4,16]	[9,10]	[10,12]	[12,14]
BAS Fun Seeking	[4,16]	[8,10]	[10,12]	[13,15]
BAS Reward Res.	[5,20]	[13,14]	[15,16]	[16,20]
Agreeableness	[4,20]	[10,13]	[14,14]	[14,18]
Conscientiousness	[4,20]	[9,12]	[12,14]	[15,20]
Extraversion	[4,20]	[11,13]	[13,15]	[15,18]
Honesty	[5,25]	[14,15]	[16,19]	[19,24]
Resiliency	[4,20]	[9,12]	[12,15]	[15,17]
Openess	[4,20]	[10,13]	[13,16]	[16,19]

B. Inter-Hemispheric Asynchrony

The EEG signals were bandpass-filtered in the range of 1-45 Hz and segmented into 17 blocks, 10 image blocks and 7 video blocks, based on the duration of each block. Each block was divided into non-overlapping epochs of 2 seconds. The frequency characteristics of the signal were determined using discrete Fourier transform as

$$X(k,e)=\sum_{n=0}^{N-1} x(n)\,w(n)\,e^{\frac{-2\pi ikn}{N}}, \qquad k=0,\dots,N-1 \quad (1)$$

where N is the length of the window (epoch), $x(n)$ is the EEG signal, $X(k,e)$ is the k^{th} harmonic corresponding to the frequency $f(k)=kF_s/N$ in the e^{th} epoch, F_s is the sampling frequency, and $w(n)$ is the window function.

The spectral data was averaged in each frequency bin in each block as

$$S(k)=\frac{1}{E}\sum_{e=1}^{E}\left|X(k,e)\right| \quad (2)$$

where E is the number of epochs in the block. The spectral data, S, was normalized with respect to the spectral energy of the preceding baseline period, giving the change in spectral power relative to the pre-stimulus period [24].

The spectral data was analyzed in the following frequency bands commonly used in clinical EEG analysis: delta (δ: 1–4 Hz), theta (θ: 4–8 Hz), alpha (α: 8–12 Hz), beta low (β_l: 12–16 Hz), beta (β: 16-20 Hz), beta high (β_h: 20–30 Hz), and gamma (γ: 30–45 Hz). The inter-hemispheric asynchrony was computed as the correlation between the mean spectral energy in the frequency bins in each block for the EEG channel pairs AF3-AF4, F3-F4, F7-F8, FC5-FC6, T7-T8, P7-P8, and O1-O2. The correlation between the channels was computed as

$$r_b = \frac{\sum\left(S_{b,l} - \bar{S}_{b,l}\right)\left(S_{b,r} - \bar{S}_{b,r}\right)}{\sqrt{\sum\left(S_{b,l} - \bar{S}_{b,l}\right)^2 \sum\left(S_{b,r} - \bar{S}_{b,r}\right)^2}} \quad (3)$$

where $S_{b,l}$ and $S_{b,r}$ represent the spectral energy in the frequency bins in the left and right hemispheres of the brain, respectively, in the frequency band b, $b = \delta, \theta, \alpha, \beta_l, \beta, \beta_h, \gamma$.

Hence, the dimensionality of the feature vector in each block was 49 (inter-hemispheric asynchrony in 7 frequency bands × 7 EEG channel pairs). The image stimuli were shown across 10 blocks with 5 categories of emotions. Features in blocks with the same category were averaged resulting in a 245 dimensional feature vector for image stimuli (49 features × 5 categories). Similarly, the feature vector for the 7 video emotions was 343 dimensional (49 features × 7 emotions). The feature vector using combined stimuli (image + video) was 588 dimensional.

C. Feature Selection and Classification

The classification models are validated using leave-one-out cross-validation (LOOCV) technique whereby every time one subject was left out for testing and the remaining subjects were used for building the machine learning prediction model. The features are standardized using mean and variance normalization in LOOCV. For feature selection, we use a method based on one-way analysis of variance (ANOVA) to identify a smaller set of discriminative features. Specifically, for each LOOCV split, we compute the *p*-value for the association *F*-test between each feature and the target class. The mean *p*-value for each feature (over all LOOCV splits) is used to select only the statistically significant features (*p*-value < 0.05).

The selected features are used to train the following four classifiers to predict personality traits: *k*-Nearest Neighbor (kNN), Logistic Regression (LR), Naïve Bayes (NB), and Support Vector Machine (SVM) with RBF kernel [25]. A separate classification model is built for each trait. The machine learning task is formulated as follows: one training example corresponds to one subject and includes the values of the selected features and the target class (personality score discretized into low, medium, or high), where the personality score is originally measured using the personality inventories. The performance of the prediction models is evaluated using the average LOOCV accuracy, that is, the ratio between the number of correct low/medium/high predictions and the total number of predictions across all 18 runs for every subject.

III. Results

The average classification accuracy values in LOOCV for personality traits prediction using image stimuli, video stimuli, and the combined (image + video) stimuli are given in Table II for the four classifiers. With each classifier, the accuracy of the video stimuli is higher than of the image stimuli, with the difference between the two ranging from 3.47% to 5.90%. This suggests that videos are a more useful stimulus than images for revealing the personality traits.

However, the best average classification accuracy is consistently achieved by the combined (image + video) stimuli. Comparing the four classifiers, we observe that with

TABLE II. Average Accuracy (%) of Predicting Personality Traits Using Different Classifiers with Image, Video, and Combined (Image+Video) Stimuli

	kNN	**LR**	**NB**	**SVM**
Image Stimuli	73.96	58.33	71.18	**83.68**
Video Stimuli	79.86	61.81	74.65	**88.19**
Combined	89.24	61.11	79.17	**95.49**

TABLE III. Accuracy (%) Using Image, Video, and Both Stimuli in Predicting Different Personality Traits Using SVM

Personality Trait	**No. of Features**	**Stimuli**		
		Image	**Video**	**Both**
Primary Psych.	(11, 17, 28)	88.89	100.00	100.00
Secondary Psych.	(8, 8, 16)	83.33	83.33	100.00
Tactics	(19, 22, 41)	94.44	100.00	100.00
Views	(4, 9, 13)	83.33	83.33	88.89
Morality	(7, 15, 22)	94.44	94.44	94.44
Narcissism	(16, 10, 26)	100.00	83.33	100.00
Mean D3	***(11, 14, 24)***	***90.74***	***90.74***	***97.22***
BIS	(12, 6, 18)	94.44	83.33	94.44
BAS Drive	(8, 12, 20)	88.89	88.89	94.44
BAS Fun Seeking	(5, 8, 13)	77.78	83.33	100.00
BAS Reward Res.	(9, 9, 18)	77.78	88.89	100.00
Mean BIS/BAS	***(9, 9, 17)***	***84.72***	***86.11***	***97.22***
Agreeableness	(7, 14, 21)	83.33	94.44	100.00
Conscientiousness	(9, 17, 26)	66.67	94.44	100.00
Extraversion	(7, 9, 16)	72.22	66.67	77.78
Honesty	(4, 12, 16)	83.33	94.44	88.89
Resiliency	(16, 9, 25)	77.78	83.33	88.89
Openess	(14, 12, 26)	72.22	88.89	100.00
Mean HEXACO	***(10, 12, 22)***	***75.93***	***87.04***	***92.59***
Mean Overall	**(10, 12, 22)**	**83.68**	**88.19**	**95.49**

the classification accuracy of 83.68% for the images, 88.19% for the videos, and 95.49% for the combined stimuli, SVM consistently yields the highest accuracy of personality trait predictions.

Table III shows the classification accuracy values obtained by SVM (the best performing classifier) for predicting each personality trait using different stimuli, with the number of selected discriminative features (reported separately for images, videos, and the combined stimuli) determined using the one-way ANOVA method. On average, 10 features are selected for the image stimuli, 12 features for videos, and 22 features for the combined stimuli. With the combined prediction accuracy of 77.78%, Extraversion is seen as the most difficult personality trait to predict. On the contrary, 9 traits are predicted perfectly with the combined stimuli, out of which Narcissism is also predicted perfectly with the image stimuli only, whereas Primary Psychopathy and Tactics are also predicted perfectly with the videos only.

Overall, we observed that inter-hemispheric asynchrony in the alpha band has the highest number of discriminative features in predicting personality traits, with 64 out of the 345 selected features. We found inter-hemispheric asynchrony in the alpha band to yield the most discriminative features in the following seven personality traits models: BAS Reward Responsiveness, Primary Psychopathy, Tactics, Narcissism, Agreeableness, Conscientiousness, and Originality.

IV. Discussion and Conclusion

This paper proposes and evaluates a method for objective detection of personality traits, as potential predictors of various mental and cognitive conditions, using EEG data. SVM, with feature selection based on ANOVA, was found to be the best performing classifier, achieving average classification accuracy of 95.49% in predicting 16 personality traits using inter-hemispheric asynchrony of the brainwaves with the combined image and video stimuli. This high accuracy demonstrates the potential of the proposed technique for predicting personality traits.

Our work builds on earlier research which showed correlation between inter-hemispheric connectivity and Agreeableness [26] and links between alpha wave activity and personality traits [27]. Our results reaffirm previous findings that the structural and functional differences in the alpha band of the two hemispheres correlate with personality.

The current work has several limitations due to the small sample of only 18 subjects. Although we employed LOOCV as an evaluation procedure, which is the best practice for small datasets, a bigger dataset should be used to better validate our findings. Also, due to the small dataset, we discretized the personality trait scores into three classes but it would be more useful to predict the values of personality traits directly, as the values within the low/medium/high groups may have different clinical meaning. In addition, the subjects recruited for this study did not exhibit extreme values of personality traits or a diagnosed medical condition. A more comprehensive dataset with a wider range of personality scores and traits will need to be collected to further validate the proposed technique.

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