Implicit User-centric Personality Recognition based on Physiological Responses to Emotional Videos

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ABSTRACT

We present a novel framework for recognizing personality traits based on users' physiological responses to affective movie clips. Extending studies that have correlated explicit/implicit affective user responses with Extraversion and Neuroticism traits, we perform single-trial recognition of the **big-five** traits from Electrocardiogram (ECG), Galvanic Skin Response (GSR), Electroencephalogram (EEG) and facial emotional responses compiled from 36 users using off-the-shelf sensors. Firstly, we examine relationships among personality scales and (explicit) affective user ratings acquired in the context of prior observations. Secondly, we isolate physiological correlates of personality traits. Finally, unimodal and multimodal personality recognition results are presented. Personality differences are better revealed while analyzing responses to emotionally homogeneous (*e.g.*, high valence, high arousal) clips, and significantly above-chance recognition is achieved for all five traits.

Categories and Subject Descriptors

H.1.2 [**User/Machine Systems**]: Human information processing; I.5.2 [**Pattern Recognition Design Methodology**]: Pattern analysis

General Terms

Measurement; Algorithms; Verification; Human Factors

Keywords

Personality recognition; Affective physiological responses

1. INTRODUCTION

The need to recognize the affective state of users for effective human-computer interaction has been widely acknowledged. Nevertheless, affect is a highly subjective phenomenon influenced by a number of contextual and psychological factors including *personality*. The relationship between individuals' personality traits and emotional responses has been actively studied by social psychologists ever since a correlation between the two was proposed in Eysenck's personality model [10]. Eysenck posited that (i) Extraversion, the personality dimension that describes a person as being either talkative or reserved, is accompanied by low cortical arousal– *i.e.*, extraverts require more external stimulation than introverts, and ii) Neurotics, characterized by negative feelings such as depression and anxiety, become very easily upset or nervous due to minor stressors, while emotionally stable persons remain composed under pressure.

Many affective studies have attempted to validate and extend Eyesenk's personality theory. Some have employed explicit user feedback in the form of affective ratings [13, 22], while others have measured implicit user responses such as Electroencephalogram (EEG) activity [27] and heart rate [9] for their analyses. However, few works have investigated affective correlations with traits other than Extraversion and Neuroticism. On the other hand, social psychology studies have primarily examined personality correlates with non-verbal social behavioral cues (see [30] for a comprehensive review), but have not attempted personality trait characterization based on emotional responses.

This paper examines the influence of personality differences on users' affective behavior as understanding the personality–affect relationship is crucial for effective emotional interaction. We try to understand the relation between emotions and personality as well as recognize it directly from the physiological signals. More specifically, we characterize both user-expressed emotions and personality traits, via heart rate, skin conductance, EEG response and facial activity patterns observed while viewing affective movie clips. We designed a study with movie clips as movies are inherently intended to evoke emotions, and movie genres such as *thriller*, *comedy* or *horror* are expressly defined by the emotions they evoke. Also, we used commercial sensors for measuring physiological responses to ensure that our study is repeatable, ecologically valid and scalable for large-scale personality recognition.

First, we study relationships between users' valence and arousal ratings provided for 36 emotional clips, and their personality scores. We then examine physiological correlates of affective and personality measures. Finally, single-trial recognition results for the five personality dimensions

ICMI '15, November 09-13, 2015, Seattle, WA, USA.

DOI: http://dx.doi.org/10.1145/2818346.2820736.

are presented. Personality recognition is attempted considering implicit user responses, the physiological signals, for (a) all movie clips, and (b) emotionally similar clips corresponding to a particular quadrant in the valence-arousal (VA) plane (*e.g.*, high valence, high arousal clips). Significantly above-chance recognition is achieved for all five traits in (b) as compared to only three in (a), implying that personality differences are better revealed on comparing affective responses to emotionally homogeneous stimuli.

Contributions. This work makes the following research contributions: (i) Personality traits have traditionally been assessed via the use of questionnaires, or by analyzing social behavior. Differently, we recognize the big-five traits by examining affective physiological responses (to our knowledge, the only other work to this end is [1]); (ii) We employ physiological signals recorded using commercial and portable sensors for recognition, which affirms the repeatability and scalability of this study; (iii) We demonstrate that personality differences are better revealed on comparing user responses to emotionally similar videos (or more generally, under similar emotion conditions).

2. RELATED WORK

This section reviews related work on (a) multimodal affect recognition, (b) personality recognition and (c) examining the personality–affect relationship.

2.1 Multimodal affect recognition

As emotions are conveyed by content creators using multiple means (audio, video), and expressed by humans in a number of ways (facial expressions, speech and phsyiological responses), many affect recognition (AR) methods employ a multimodal framework. Content-based AR works utilize audio, video and audio–visual cues (see [32] for a review). Recent AR methodologies have focused on the user and leveraged the use of physiological sensors (*e.g.*, EEG, ECG, GSR) for efficient emotion representation. Emotions induced by music clips are recognized via heart rate, muscle movements, skin conductivity and respiration changes in [14]. Lisetti and Nasoz [18] use affective clips and mathematical equations to elicit emotions, and use GSR, heart rate and temperature signals to recognize them. Koelstra *et al.* [15] analyze blood volume pressure, respiration rate, skin temperature and Electrooculogram (EOG) patterns for recognizing the level of valence and arousal induced by music videos. Implicit user-centered AR from visual, speech, physiological and eye-gaze patterns is discussed in [25]. Abadi *et al.* [3] study Magnetoencephalogram (MEG), Electromyogram (EMG), EOG and ECG responses from users for music and movie clips, and observe that movie clips are better for emotion elicitation and AR.

2.2 Personality recognition

The big-five or the five-factor model [8] describes human personality in terms of five dimensions – Extraversion (*sociable* vs *reserved*), Neuroticism or the degree of emotional stability (*nervous* vs *confident*), Agreeableness (*compassionate* vs *dispassionate*), Conscientiousness (*dutiful* vs *easy-going*) and Openness (*curious/creative* vs *cautious/conservative*). A comprehensive survey of personality computing approaches is presented in [30]. The traditional means to measure personality dimensions are questionnaires or self-reports [20]. Argamon *et al.* [4] pioneered automated personality recognition using lexical cues from informal texts for recognizing Extraversion (*Ex*) and Neuroticism (*Neu*). Olguin *et al.* [23] show that non-verbal behavioral measures acquired using a sociometric badge such as the amount of speech and physical activity, number of social interactions and physical proximity to other objects is highly correlated with personality. Much work has since employed non-verbal social behavioral cues for personality recognition including [17], where *Ex* is recognized using speech and social attention cues in round-table meetings, and [28, 31] which estimate *Ex* and *Neu* from proxemic and attention cues in party settings. Among works that attempt to recognize the big-five traits, Mairesse *et al.* [19] use acoustic and lexical features, while Srivastava *et al.* [26] automatically complete personality questionnaires for 50 movie characters utilizing lexical, audio and visual behavioral cues. Similar cues are used in [5] for trait recognition from self-presentation videos.

2.3 Personality-Affect relationship

The relationship between personality traits and emotional responses has been extensively studied in social psychology, but hardly in a computational setting. Eysenck's seminal personality theory [10] posits that extraverts require more external stimulation than introverts, and that neurotics are aroused more easily. Many psychology studies have since examined the personality–affect relationship by studying explicit or implicit user responses. Personality effects on brain activation related to valence and arousal is investigated in [13]. Based on functional magnetic resonance imaging (fMRI) responses, this study concludes that *Neu* level correlates negatively with valence, and positively with arousal. In an EEG-based study relating personality and arousability [27], a negative correlation is observed between *Ex* and arousal, while positive correlation between *Neu* and arousal is noted for negative stimuli. The impact of personality traits on affective user ratings is studied using path analysis in [29]. Feedback scores from 133 students are analyzed in [22] to conclude that neurotics experience positive emotions similar to emotionally stable counterparts in pleasant situations even though they may experience negative emotions more strongly. Event-related potentials (ERPs) and heart rate changes are studied in [9] to confirm a positive correlation between *Neu* and arousal for negative stimuli, while signal-detection is used in [11] to conclude that extraverts are generally less aroused than introverts.

Examining the above studies, it is evident that hardly any of them have ventured beyond the *Ex* and *Neu* traits. The only work to recognize the big-five traits from affective responses is that of Abadi *et al.* [1], and our work is closest to theirs in this respect. Nevertheless, we consider user responses to a larger stimulus set (36 clips vs 16 in [1]), and show superior personality recognition by comparing affective user responses to emotionally similar clips.

3. METHODOLOGY

An overview of our personality recognition framework is presented in Fig. 1 (left). To study the personality–affect relationship, we performed a study where users' physiological responses were recorded as they viewed 36 affective movie clips used in [2]. Explicit feedback in the form of *arousal*, *valence*, *liking*, *engagement* and *familiarity* ratings was obtained after they viewed each movie clip but only arousal and valence ratings are analysed in this study. Users' per-

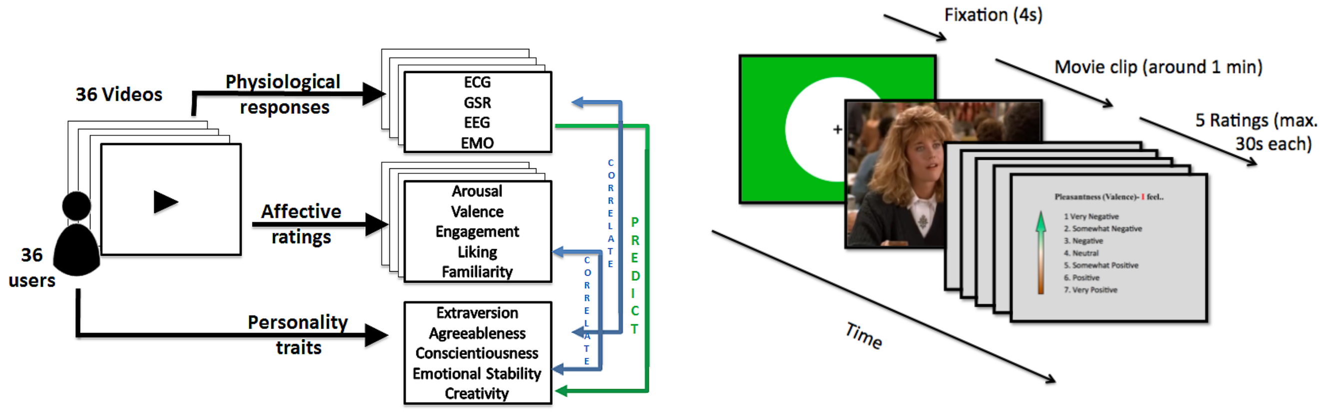


Figure 1: (left) User study overview. (right) Timeline for each trial.

sonality measures for the big-five dimensions were compiled using a big-five marker scale (BFMS) questionnaire [24].

3.1 Materials and methods

Subjects: 36 university students (mean age = 29.2, 12 female) of various nationalities participated in our study. All subjects were fluent in English and were habitual Hollywood movie watchers.

Materials: One PC with two monitors was used for the experiment. One monitor was used for video clip presentation at 1024×768 pixel resolution with 60 Hz screen refresh rate, and was placed roughly one meter in front of the user. The other monitor allowed the experimenter to check the recorded sensor data. Following informed consent, physiological sensors were positioned on the user's body as shown in Fig. 2(a). The GSR sensor was tied to the left wrist, and two electrodes were fixed to the index and middle finger phalanges. Two measuring electrodes for ECG were placed at each arm crook, with the reference electrode placed at the left foot. A single dry-electrode EEG device was placed on the head like a normal headset, with the EEG sensor touching the forehead and the reference electrode clipped to the left ear. EEG data samples were logged using the `Lucid Scribe` software, and all sensor data were recorded via bluetooth. Also, a webcam was used to record facial activity. Synchronized data recording, pre-processing and analyses were performed using MATLAB Psychtoolbox[1].

Protocol: Each user performed the experiment in a session lasting about 90 minutes. Viewing of each movie clip is denoted as a trial. After two practice trials involving clips that were not part of the actual study, users watched movie clips randomly shown in two blocks of 18 trials, with a short break in-between to avoid fatigue. In each trial (Fig. 1(right)), a fixation cross was displayed for four seconds followed by clip presentation. On viewing each clip, users provided their affective ratings within a time limit of 30 seconds as described below. Participants also completed a personality questionnaire after the experiment.

Stimuli: We adopted the 36 movie clips used in [2] for our study. These clips are between 51–127 sec long (μ =80, σ =20), and are shown to be uniformly distributed (9 clips per quadrant) over the VA plane.

[1]http://psychtoolbox.org/

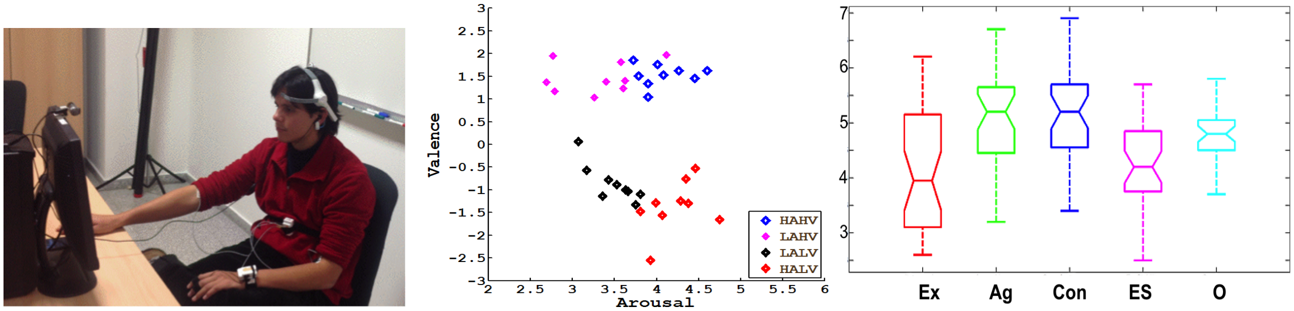
Affective ratings: For each movie clip, we compiled valence (V) and arousal (A) ratings reflecting the user's first impression. A 7-point scale was used with a -3 (*very negative*) to 3 (*very positive*) scale for V, and a 0 (*very boring*) to 6 (*very exciting*) scale for A. Ratings concerning *engagement*, *liking* and *familiarity* were also acquired, but are not analyzed in this work. Mean user VA ratings for the 36 clips are plotted in Fig. 2(b), and are color coded based on the associated categories from the ground-truth ratings from [2]. Ratings form a C-shape in the VA plane, similar to prior affective studies [2,15].

Personality scores: Participants also completed the big-five marker scale (BFMS) questionnaire [24] which has been used in many personality recognition works [17,28,31]. Personality measure distributions along the five traits are shown in Fig. 2(c).

3.2 Physiological feature extraction

We extracted affective physiological features corresponding to each trial over the final 50 seconds of stimulus presentation, owing to two reasons: (1) The clips used in [3] are not emotionally homogeneous, but are more emotional towards the end. (2) Some employed features (see Table 1) are nonlinear functions of the input signal length, and fixed time-intervals needed to be considered as the movie clips were of varying lengths. A brief description of the different physiological signals analyzed in this work are as follows.

Galvanic Skin Response (GSR). GSR measures transpiration rate of the skin. When two electrodes are positioned on the middle and index fingers' phalanges and a small current is sent through the body, resistance to current flow changes with the skin transpiration rate. Most of the GSR information is contained in low-frequency components, and the signal is recorded at 100 Hz sampling frequency with a commercial and portable bluetooth sensor. Following [14,15,25], we extracted 31 GSR features listed in Table 1.



(a) (b) (c)

Figure 2: (a) Participant with sensors (EEG, ECG and GSR visible) during the experiment, (b) Mean Valence-Arousal (VA) ratings for the 36 movie clips used in our study and (c) Box-plots showing distribution for 36 users of the big-five personality trait scores Extroversion (Ex), Agreeableness (Ag), Conscientiousness (Con), Emotional Stability (ES) and Openness (O).

Table 1: Extracted features for each modality (feature dimension stated in parenthesis). *Statistics* denote mean, standard deviation (std), skewness, kurtosis of the raw feature over time, and % of times the feature value is above/below mean±std.

Modality	Extracted features
ECG (32)	Ten low frequency ([0-2.4] Hz) power spectral densities (PSDs), four very slow response (VSR [0-0.04] Hz) PSDs, IBI, HR and HRV statistics.
GSR (31)	Mean skin resistance and mean of derivative, mean differential for negative values only (mean decrease rate during decay time), proportion of negative derivative samples, number of local minima in the GSR signal, average rising time of the GSR signal, spectral power in the [0-2.4] Hz band, zero crossing rate of skin conductance slow response (SCSR) [0-0.2] Hz, zero crossing rate of skin conductance very slow response (SCVSR) [0-0.08] Hz, mean SCSR and SCVSR peak magnitude
Frontal EEG (88)	Average of first derivative, proportion of negative differential samples, mean number of peaks, mean derivative of the inverse channel signal, average number of peaks in the inverse signal, statistics over each of the 8 signal channels provided by the Neurosky software
EMO (72)	Statistics concerning horizontal and vertical movement of 12 motion units (MUs) specified in [12].

Electroencephalography (EEG). EEG measures small changes in the skull's electrical field produced by brain activities, and information is encoded in the EEG signal amplitude as well as in certain frequency components. We used a commercial, single dry-electrode EEG sensor[2], which records eight information channels sampled at 32 Hz. The recorded information includes frontal lobe activity, level of facial activation, eye-blink rate and strength, which are relevant emotional responses.

Electrocardiogram (ECG). Heart rate characteristics have been routinely used for user-centered emotion recognition. We performed R-peak detection on the ECG signal to compute users' inter-beat intervals (IBI), heart rate (HR), and the heart rate variability (HRV). We also extracted power spectral density (PSD) in low frequency bands as in [14,25].

Facial landmark trajectories (EMO). A facial feature tracker [12] was used to compute displacements of 12 interest points or motion units (MU) in each video frame. We calculated 6 statistical measures for each landmark to obtain a total of 72 features (Table 1).

4. PERSONALITY SCORES VS RATINGS

We now examine relationships among user valence (V) and arousal (A) ratings and their personality trait scores in the context of previous hypotheses put forth in literature. To this end, we (i) computed correlations between users' personality scales and VA ratings for each movie clip, and determined significant correlations according to Fisher's method (Table 2), and ii) dichotomized personality measures based on the median score to determine *high*/*low* trait groups (*e.g.*, extraverts and introverts), and studied the affective ratings of each group.

Table 2: Mean correlations between personality scales and user VA ratings for all movie clips. * denotes significant correlations (p<0.01) obtained using Fisher's method.

	Ex	Ag	Con	ES	Open
Arousal	-0.15*	-0.05	-0.04	0.07	-0.08*
Valence	0.22*	0.16	-0.06	0.08	0.15

4.1 H1: Extraversion vs Arousal and Valence

The correlation between Extraversion and arousal has been investigated in many studies– EEG measurements in [27], signal detection analysis in [11], and fMRI [13] have shown lower arousal in extraverts as compared to introverts, consistent with Eyesenck's personality theory. Also, Extraversion has been found to correlate with positive valence in a number of works [7].

Correlation analyses presented in Table 2 confirm a slight but significant negative correlation between *Ex* and A as noted in the literature. Likewise, a significant positive correlation is noted between *Ex* and V mirroring prior findings. Therefore, our data corroborates previous observations connecting Extraversion and affective behavior.

[2]www.neurosky.com

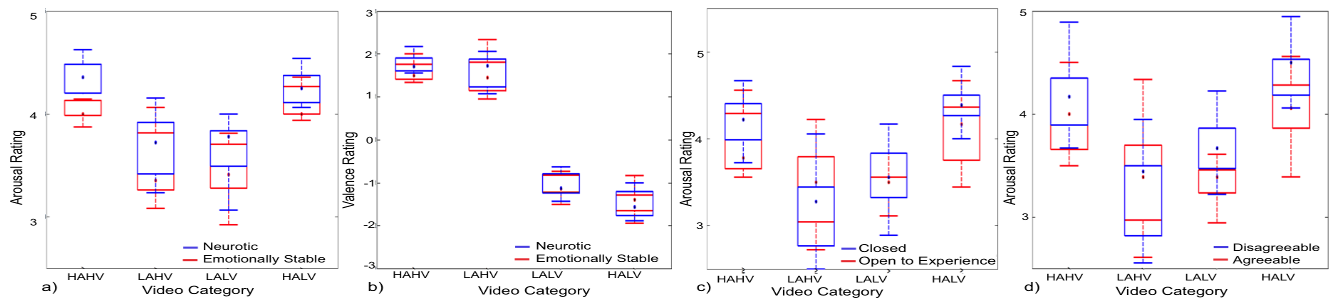


Figure 3: Quadrant-wise comparisons of A,V ratings for Neurotics vs emotionally stable subjects are shown in (a,b). Arousal rating comparisons for (c) Open vs Closed, and (d) Agreeable vs Disagreeable subjects.

4.2 H2: Neuroticism vs Arousal

The relationship between Neuroticism and A has been extensively studied and commented on– a positive correlation between *Neu* and A is revealed through fMRI responses [13], and EEG analysis [27] reinforces this observation especially for negative valence stimuli. [22] further remarks that neurotics experience negative emotions stronger than emotionally stable persons.

As no significant correlation is observed between *Neu* scores and A ratings in Table 2, we used t-tests to compare mean A ratings provided by the neurotic and emotionally stable (*ES*) groups upon dichotomization of the *Neu* scale by thresholding at the median score (which was midway between the extremes, resulting in equal-sized groups). To examine if our data suggested a positive correlation between *Neu* and A, we performed a left-tailed t-test comparing the A ratings of the *ES* and neurotic groups– the test revealed a significant difference in A ratings for high arousal clips ($t(34) = -1.8058, p = 0.0399$), and a marginally significant difference for low arousal clips ($t(34) = -1.4041, p = 0.0847$).

Quadrant-wise distributions of A ratings for the *ES* and neurotic groups are presented in Fig. 3(a). Quadrant-wise comparisons show that neurotics generally experience higher arousal than *ES* subjects. Left-tailed t-tests confirm that neurotics provided significantly higher A ratings for HAHV ($t(16) = -2.5828, p < 0.0100$) clips, and marginally higher A ratings for LALV ($t(16) = -1.6077, p = 0.0637$) and HALV ($t(16) = -1.3859, p = 0.0924$) stimuli. No difference was however observed for LAHV clips ($t(16) = -0.9946$, n.s.). In general, our analyses support the observation that Neuroticism is associated with higher arousal.

4.3 H3: Neuroticism vs Valence

Differing observations have been made regarding the relationship between Neuroticism and valence. A negative correlation between *Neu* and positive valence is observed in [13], while a positive relationship between the two for low arousal stimuli is noted in [29]. [22] remarks that the *Neu*-V relation is moderated by situation– while neurotics may feel less positive in unpleasant situations, they experience positive emotions as strongly as *ES* subjects in pleasant conditions.

Again, as no significant correlation between *Neu* and V is noted in Table 2, we focus on V ratings of the neurotic and *ES* groups. Very similar V ratings are noted for high/low valence clips. Quadrant-wise V rating comparisons (Fig. 3(b)) reveal that neurotics feel slightly more positive than *ES* subjects on viewing HAHV clips but the difference is not significant ($t(16) = -1.489, p = 0.1558$) clips. Overall, our analyses do not reveal any definitive relationship between *Neu* and valence.

4.4 H4: Openness vs Arousal and Valence

Among the few works to study Openness, [29] notes a positive correlation between Openness and valence under low arousal conditions, which is attributed to the intelligence and sensitivity of creative individuals[3], enabling them to better appreciate subtly emotional stimuli.

To examine this hypothesis, we used right-tailed t-tests comparing V, A ratings of the groups *open* and *closed* to experience upon dichotomization. Very similar valence ratings are noted for the *open* and *closed* groups. Quadrant-based comparisons reveal that open individuals experienced only slightly higher valence while viewing LAHV clips ($t(16) = 1.4706, p = 0.0804$).

Note the significant and slightly negative correlation between Openness and A from Table 2. Focusing on A ratings of the *open* vs *closed* groups, marginally different A ratings ($t(34) = -1.5767, p = 0.0621$) are noted for high arousal stimuli. For fine-grained analysis, we again used left-tailed t-tests for quadrant based comparisons (Fig. 3(c)), which reveal that *closed* individuals experienced significantly higher arousal for HALV clips ($t(16) = -1.9834, p = 0.0324$), and slightly higher arousal for HAHV clips ($t(16) = -1.5402, p = 0.0715$). In summary, we observe a negative relationship between Openness and arousal, and a slightly positive relationship between Openness and valence as noted in [29].

4.5 Agreeableness and Conscientiousness

Comparison of arousal ratings of the *agreeable* and *disagreeable* groups (Fig. 3(d)) revealed that *agreeable* individuals are generally less aroused by LV videos ($t(34) = -2.1859, p = 0.0358$). Quadrant-based analyses also show that *disagreeable* individuals felt more aroused by HALV ($t(16) = -2.5493, p = 0.0214$) and marginally more aroused for LALV ($t(16) = -2.0976, p = 0.0522$) clips. Conscientiousness scale differences did not significantly influence the VA ratings in any manner.

5. PERSONALITY RECOGNITION FROM PHYSIOLOGICAL SIGNALS

In Sec. 4, a direct correlation with affective ratings is only noted for the Extraversion and Openness personality traits. For the other traits, the influence of personality differences

[3] Creativity strongly correlates with Openness [21].

Table 3: Physiological correlates of emotion and personality. R° denotes the number of significant feature correlates, while R^2 is the coefficient of determination for the regression model with the significant correlates as predictors. Bold values denote linear regression models with a significant R^2 statistic.

		Arousal		**Valence**		**Extra.**		**Agreeable**		**Conscient**		**Em. Stab.**		**Open**	
Video Set	Feature	R^o	R^2	R^o	R^2	R^o	R^2	R^o	R^2	R^o	R^2	R^o	R^2	R^o	R^2
All	**ECG**			1	**0.17**	2	0.51					1	0.49	1	0.35
	GSR														
	EMO													1	**0.28**
	EEG	1	0.45	1	0.27	2	0.66	2	0.64	2	**0.68**	2	0.54	2	0.49
HAHV	**ECG**					1	0.46					1	0.45		
	GSR														
	EMO			1	0.59							3	0.75	3	0.77
	EEG			1	0.49	2	0.54							1	0.50
LAHV	**ECG**			1	**0.15**	3	0.55			1	0.44	1	0.46	1	0.42
	GSR														
	EMO	1	**0.20**			1	0.30	1	0.29					2	**0.51**
	EEG	1	0.54											1	0.56
LALV	**ECG**	1	0.41			2	0.55					1	0.44	1	0.42
	GSR														
	EMO			1	0.22	2	0.61	1	0.40					2	0.45
	EEG			1	0.40	1	0.57			3	0.63	1	0.58		
HALV	**ECG**											2	0.57		
	GSR														
	EMO													1	**0.13**
	EEG			1	**0.59**	3	**0.69**			2	0.53			1	0.39

Table 4: Personality recognition performance considering affective responses to a) all, and b) emotionally homogeneous stimuli. Maximum F1-scores with unimodal and multimodal methods are shown in bold.

		Extravert		**Agreeable**		**Conscient**		**Em. Stab**		**Open**	
Videos	**Method**	**acc**	**F1**	**acc**	**F1**	**acc**	**F1**	**acc**	**F1**	**acc**	**F1**
All	**ECG**	0.45	0.43	0.42	**0.37**	0.45	**0.31**	0.52	**0.50**	0.55	0.54
	GSR	0.15	0.14	0.42	0.34	0.39	0.28	0.24	0.20	0.91	**0.91**
	EMO	0.61	**0.59**	0.42	0.34	0.12	0.11	0.42	0.37	0.27	0.26
	$\mathbf{W_{est}^t}$	0.61	**0.60**	0.42	**0.39**	0.45	**0.31**	0.64	**0.63**	0.91	**0.91**
HAHV	**ECG**	0.69	**0.69**	0.75	0.75	0.19	0.18	0.63	**0.63**	0.06	0.06
	GSR	0.59	0.59	0.78	0.78	0.25	0.25	0.31	0.29	0.78	**0.78**
	EMO	0.31	0.31	0.84	**0.84**	0.41	**0.41**	0.47	0.44	0.22	0.21
	EEG	0.09	0.09	0.72	0.72	0.34	0.34	0.41	0.39	0.53	0.53
	$\mathbf{W_{est}^t}$	0.78	**0.78**	0.84	**0.84**	0.56	**0.56**	0.69	**0.69**	0.78	**0.78**
HALV	**ECG**	0.45	0.45	0.76	**0.76**	0.34	0.26	0.45	0.41	0.55	0.55
	GSR	0.72	**0.72**	0.72	0.72	0.55	0.55	0.21	0.19	0.69	**0.69**
	EMO	0.38	0.34	0.38	0.37	0.38	0.34	0.52	**0.51**	0.62	0.62
	EEG	0.34	0.32	0.24	0.23	0.69	**0.69**	0.31	0.29	0.62	0.61
	$\mathbf{W_{est}^t}$	0.72	**0.72**	0.79	**0.79**	0.76	**0.76**	0.55	**0.54**	0.69	**0.69**
LAHV	**ECG**	0.45	0.39	0.32	0.31	0.42	0.34	0.55	0.45	0.58	0.56
	GSR	0.32	0.27	0.45	0.44	0.42	0.34	0.42	0.30	0.77	**0.77**
	EMO	0.65	**0.63**	0.26	0.23	0.65	**0.64**	0.65	**0.63**	0.29	0.25
	EEG	0.32	0.30	0.65	**0.63**	0.65	0.62	0.52	0.52	0.68	0.67
	$\mathbf{W_{est}^t}$	0.68	**0.67**	0.68	**0.67**	0.65	**0.64**	0.74	**0.74**	0.81	**0.81**
LALV	**ECG**	0.50	**0.49**	0.20	0.20	0.13	0.13	0.37	0.27	0.30	0.29
	GSR	0.27	0.26	0.23	0.23	0.33	**0.33**	0.60	0.57	0.63	**0.63**
	EMO	0.43	0.43	0.47	**0.46**	0.27	0.27	0.30	0.26	0.17	0.16
	EEG	0.33	0.33	0.00	0.00	0.10	0.10	0.67	**0.66**	0.37	0.35
	$\mathbf{W_{est}^t}$	0.57	**0.54**	0.53	**0.53**	0.33	**0.33**	0.70	**0.69**	0.63	**0.63**

on users' affective behavior is only revealed via quadrant-wise comparisons, where affective ratings of the *high* and *low* trait groups for emotionally similar (or homogeneous) stimuli are examined. While affective ratings represent an explicit reflection of one's emotional state, it would be reasonable to expect affective physiological responses, to also reveal personality differences as they implicitly convey the same information. We therefore examined correlations between physiological features, affective ratings and personality traits (Table 3), and attempted personality recognition (Table 4) considering responses to (a) all, and (b) emotionally similar clips.

5.1 Correlation analyses

We attempted to discover physiological correlates of emotional and big-five personality attributes via partial Pearson correlations. Given the large number of extracted physiological features (Table 1) as compared to the population size for this study, we first performed a principal component analysis (PCA) on features to avoid overfitting, and retained those components that explained 99% of the variance. Table 3 presents correlations between these principal components, and users' affective ratings and personality scales. For each of the modalities, we determined components that significantly correlated with the personality scales for the five dimensions (R° denotes number of significant correlates). For affective dimensions, we determined significant correlates considering mean V,A ratings provided by all users for the 36 clips. We also trained regression models with the significantly correlating components as predictors of the dependent emotion/personality variable, and the squared correlations of these models (R^2) are also tabulated.

Considering correlations with arousal and valence, while only few correlates are observed possibly owing to the nature of the sensors used in this study, more correlates are observed for V than for A overall. At least one significant correlate is noted for all modalities except GSR. EEG is the modality found to correlate most with A, with one correlate observed for all and LAHV movie clips. EEG also has the most number of correlates with V (one significant correlate per video set), but this is unsurprising as a number of works have successfully recognized V with commercial-grade sensors [6]. For V, one ECG correlate is noted for all and LAHV videos, and one Emo correlate for HAHV and LALV videos. Prior studies [3, 15] have also noted that these modalities correlate better with V than A.

Focusing on personality dimensions, a larger number of physiological correlates are observed as compared to emotional attributes. Least number of correlates are noted for Agreeableness, while most correlates are noted for Extraversion. The EEG modality corresponds the maximum number of correlates, while no correlates are observed for GSR. In general, a larger number of physiological correlates are noted for emotionally similar videos for all traits except Agreeableness. Also, models with a higher R^2 statistic are noted for similar clips, implying that physiology–based linear models can more effectively predict personality traits while comparing user responses under similar affective conditions.

5.2 Recognition results

Recognition accuracies and F1-scores achieved using the above-computed physiological features for the five personality dimensions are presented in Table 4. Linear SVMs and leave-one-user-out cross-validation were used, and the late multimodal fusion technique proposed in [16] was used to improve on the unimodal results. Multimodal results are denoted using $\mathrm{W}^{\mathrm{t}}_{\mathrm{est}}$ where the test sample label is computed as $\sum_{i=1}^{4} \alpha_i^* t_i p_i$. Here, i indexes the four modalities used in this work, p_i's denote posterior SVM probabilities, $\{\alpha_i^*\}$ are the optimal weights maximizing the F1-score on the training set and $t_i = \alpha_i F_i / \sum_{i=1}^{4} \alpha_i F_i$, where F_i denotes the F1-score obtained on the training set with the i^{th} modality.

Upon dichotomizing the personality scores based on the median, an inexact split (19 vs 17) was obtained only for the Conscientiousness and Openness traits. Therefore, baseline accuracy/F1-score for these two traits is 0.53, while being 0.5 for the others. Considering affective responses to all videos, greater-than-chance recognition is achieved only for three traits (excepting Agreeableness and Conscientiousness). When physiological responses to emotionally similar videos are considered, the best unimodal F1-scores for all personality traits are above-chance with the exception of facial activity features for Conscientiousness. These results confirm that personality differences between users with high and low traits are better revealed on comparing their affective responses to emotionally similar clips. Consistently high recognition performance is achieved for the Openness trait, and also for Agreeableness considering homogeneous videos. Conscientiousness is the most difficult trait to recognize using the considered physiological features, and generally low recognition performance is also noted for Neuroticism. Focusing on the sensing modalities, GSR consistently produces the best performance for Openness while ECG performs best for Agreeableness in three out of five conditions.

6. DISCUSSION & CONCLUSION

We performed personality trait recognition from emotional user responses recorded using commercial sensors. This paper represents one of the first works to extend Eyesenck's observations relating personality traits and emotional behavior in a computational setting. Also, the use of commercial sensors ensures that the study is ecologically valid and scalable. Analyzing relationships between users' affective ratings and personality traits, Extraversion is found to be positively correlated with valence and negatively correlated with arousal. Also, quadrant-based analysis reveals that Neuroticism is associated with higher arousal, in line with prior observations.

We then computed physiological correlates of personality, and physiological features are found to correlate better with personality trait scales when user responses to emotionally homogeneous videos are considered. Also, considerably better-than-chance recognition is achieved for all personality traits considering homogeneous clips (excepting Conscientiousness considering LALV clips). These results confirm that personality differences are better revealed when emotional responses to similar clips are considered, in line with the statistical analyses. Best recognition results are obtained for Openness and Agreeableness, while worst performance is noted for Conscientiousness.

It is pertinent to point out some limitations of our analyses and study in general. Weak linear correlations are noted between emotional and personality attributes in Table 2, and only few physiological correlates of emotion and personality are observed in Table 3, implying that the personality–affect relationship may not be best captured via linear correlations. Nevertheless, some patterns do emerge from the presented analyses. Maximum number of physiological correlates are noted for Openness, and the best recognition performance is also achieved for this trait. Also, some correlation was noted between emotional attributes and personality traits with the exception of Conscientiousness in Section 4, and least recognition performance is obtained for this trait. Overall, promising personality trait recognition is achieved with the proposed framework employing inexpensive, portable and commercial sensors. Finally, we will also make the compiled data publicly available for furthering related research.

7. ACKNOWLEDGEMENTS

This research was funded by the HCCS research grant from Singapore's Agency for Science, Technology and Research (A*STAR), the FP7 European Project xLiMe and SensAura Tech.

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