Addressing Subject-dependency for Affective Signal Processing
Modeling Subjects' Idiosyncracies

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Keywords: Affective Signal Processing, Subject-dependency, Psychophysiological Inference, Personality.

Abstract: Most works on Affective Signal Processing (ASP) focus on user-dependent emotion recognition models which are personalized to a specific subject. As these types of approach have good accuracy rates, they cannot easily be reused with other subjects for industrial or research purposes. On the other hand, the reported accuracy rates of user-independent models are substantially lower. This performance decrease is mostly due to the greater variance in the physiological training data set drawn from multiple users. In this paper, we propose an approach to address this problem and enhance the performance of user-independent models by explicitly modeling subjects' idiosyncrasies. As a first exemplification, we describe how personality traits can be used to improve the accuracy of user-independent emotion recognition models. We also present the experiment that will be carried on to validate the proposed approach.

1 INTRODUCTION

This paper focuses on the subfield of physiological computing that aims to infer subjects' psychological states based on their physiological signals (Fairclough, 2009). When the psychological states are related to emotions, the literature often refers to this process as Affective Signal Processing (ASP) (van den Broek et al., 2009a). At a theoretical level, ASP is based on the principle of psychophysiological inference (Cacioppo and Tassinary, 1990), which can be defined as follows: let ψ be the set of psychological constructs (e.g. emotional arousal, cognitive load) and Φ be the set of physiological variables (e.g. heart rate, pupil dilation). The psychophysiological inference is then described according to the following equation:

$$\Psi = f(\Phi) \quad (1)$$

Most works aiming at implementing the physiological inference process are using a machine learning framework (Picard et al., 2001; Christie and Friedman, 2004; Haag et al., 2004; Bamidis et al., 2009; Chanel et al., 2009; Verhoef et al., 2009; Kolodyazhniy et al., 2011). Despite interesting results, reported prediction accuracy rates are still below the level of other machine learning problems and cannot feed real-world applications (van den Broek et al., 2010a). Among the different challenges that have been identified to further develop ASP, this paper addresses the problem of subject-dependency (van den Broek et al., 2010b).

In machine learning, a model's *generalizability* represents its capacity to perform a valid inference on a new and unseen data point (Bishop, 2006). The generalization error, empirically estimated on a large data set, therefore represents the model's performance. Specifically to the context of ASP, a model's *genericity* represents its capacity to perform a valid inference on a previously unseen subject. Genericity is then used to describe the range of subjects onto which a model applies. Two types of emotion recognition models are defined in regards to their genericity (Villon and Lisetti, 2007).

1. **User-dependent:** the training set contains data from one participant and the test set contains new data from the same participant.
2. **User-independent:** the training set contains data from many subjects and the test set contains data from new subjects.

A recent review by Novak et al., (2012) reports that most works on psychophysiological inference have focused on subject dependent approaches.

Courtemanche F., Campbell E., Léger P. and Lepore F..
Addressing Subject-dependency for Affective Signal Processing - Modeling Subjects' Idiosyncracies.
DOI: 10.5220/0005330700720077
In *Proceedings of the 2nd International Conference on Physiological Computing Systems* (PhyCS-2015), pages 72-77
ISBN: 978-989-758-085-7

Furthermore, as shown in Table 1, a "genericity vs generalizability" dilemma appears to be present at the heart of ASP, as user-dependent models have better results than non-dependent.

Schuster et al., (2012) investigated the difference between the two types of model. They used a recognition model based on Support Vector Machines to differentiate three emotional valence levels (negative, neutral and positive) using electroencephalographic signals. The model was trained twice on the same dataset (n = 18 subjects) according to the type 1 and 2 protocols. Their results showed a significant difference of the generalization error between the two protocols, the subject dependent approach obtaining a better performance. Bailenson et al., (2008) also obtained better accuracy results for user-dependent models when comparing the two types of approach using facial and physiological data. In another study, Bock et al., (2012) showed that the performance difference between user-dependent and user-independent models is greater for recognition models based on physiological signals than for models based on voice analysis. The principal reason explaining the poorer performance of subject independent approaches is the great variability of physiological signals observed between different subjects. Training a model to recognize emotional reactions of a single subject thus allows avoiding this problem. The subject's psychophysiological specificities are, in some way, learned by the model.

Table 1: Emotion recognition models comparison. UD stands for user-dependent models and UI stands for user-independent models.

Authors	Elicitor	Genericity	Generalizability (%)
Chanel et al. (2009)	Recollection	**UD**	67
Hristova et al. (2009)	IAPS	**UD**	96,9
Benovoy et al. (2007)	Acting	**UD**	90
Picard et al. (2001)	Acting	**UD**	81
Rani et al. (2006)	Cognitive, games	**UD**	85,81
Cheng (2012)	Songs	**UD**	95,97
Kulkolja et al. (2014)	IAPS	**UD**	60,3
Wu et al. (2010)	Simulator	**UD + UI**	95,5 (UD) - 36,9 (UI)
Kim et al. (2004)	audio, visual, cognitive	**UI**	61,8
Kolodyazhniy et al. (2011)	Film	**UI**	77,9
Verma et al. (2014)	Music videos	**UI**	85
Chang et al. (2013)	Movies	**UI**	89,2

However, even though subject dependent models are currently more performant, they have many pragmatic drawbacks. The most important being that user-dependent models require a time-consuming training phase before being operational. For industrial or scientific applications, it implies that every new subject must go through the complete training process (i.e. training stimuli presentation, physiological recordings, etc.). This requirement represents a significant burden, as most training procedures take an important amount of time and sometimes include strong emotional cues (e.g. IAPS images, movie clips). On the other hand, after the initial training phase, subject-independent models don't need to be specifically adapted to new subjects.

The current literature on psychophysiological inference calls out for the development of more efficient subject-independent approaches (AlZoubi et al., 2012; Schuster et al., 2012; van den Broek et al., 2010b). This paper therefore aims to bring a contribution to the development of such generic approaches. The remainder of the paper is as follow: In section 2, we present the general framework of the proposed approach that aims at explicitly modeling subjects' idiosyncrasies. In section 3, we describe how the theory of individual response specificity can be used to fulfill such a goal. In section 4, we briefly describe the experiment that will be carried on to validate the proposed approach. Concluding remarks are given is section 5.

2 MODELING IDIOSYNCRASY

The main cause of the "genericity vs generalizability" dilemma in ASP is related to the idiosyncrasy of emotional reactions. Simply stated, each person reacts differently to a same stimulus, at both the physiological and subjective level. A same situation can therefore generate different emotions, and a same emotion can generate different physiological signals. Both outcomes have been shown to be deleterious to user-independent recognition models (Villon and Lisetti, 2007). On the other hand, user-dependent recognition models do not need to model the idiosyncratic factors at play in the f relationship (see equation 1) as they remain constant for a same subject. Let equation 2 represent a simple emotion prediction model based on linear regression and two physiological signals (Φ_1 and Φ_2).

$$\Psi = \beta_1\Phi_1 + \beta_2\Phi_2 \quad (2)$$

The model's parameters (β) are simply optimized to best fit the targets for a given subject (e.g. subject's arousal level). The subject's idiosyncrasies are therefore learned implicitly within β_1 and β_2. For example, the specific way in which Φ_1 reflects emotion intensity for a subject is model by β_1. It can explain, in part, why when applied to a different subject (with different idiosyncrasies), the model's performance decreases. As illustrated in Figure 1, we suggest to explicitly model subjects' idiosyncrasies in order for user-independent models to better adapts to different subjects.

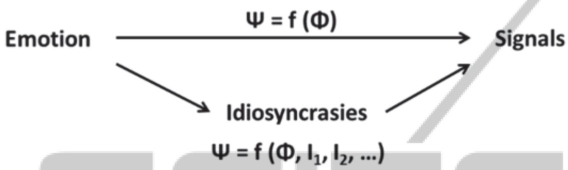

Figure 1: Modeling idiosyncracies.

As modeled in equation 3, the implicit idiosyncratic factors would be extracted from β_1 and β_2 to explicit parameters β_i.

$$\Psi = \beta_1\Phi_1 + \beta_2\Phi_2 + \beta_3 I_1 + \beta_4 I_2 \ldots \quad (3)$$

There are different ways in which idiosyncratic factors can be modeled and taken into account in ASP. Following the previous example, β_3 could model the way in which an idiosyncratic factor I_1 (e.g. a phobia or anxiety trait) mediate the way in which Φ_1 reflects emotion intensity for a given subject. This specific effect of I_1, that was initially implicit in β_1, would now be explicit in β_3. Some research have explored this avenue by using subjects' characteristics. For example, Frantzidis et al., (2010) have integrated the subjects' gender in an emotional arousal recognition model based on decision trees and electroenphalographic (EEG) data. Zhou et al., (2011) have used subjects' culture and gender in order to compare the generalisation error of different training protocols. They used three different models (decision tress, k-nearest neighbors, and decomposition trees) to classify seven discrete emotions using electrodermal activity, electromyography, respiration, and EEG data. Results showed that training on gender based subgroups "male'' (n = 21) and ''female'' (n= 21), lead to better performance. They obtained similar results using models trained on culture based subgroups ''Chinese'' (n = 14), ''Indian'' (n = 14) and ''Western'' (n = 14). These results show that a subject-independent model can achieve better results when the training set is narrowed using subjects' characteristics.

3 INDIVIDUAL RESPONSE SPECIFICITY

We used the Individual Response Specificity theory (IRS) (Marwitz and Stemmler, 1998) as a framework to model the subjects' idiosyncrasies. The IRS can be defined as *''the tendency of subjects to present similar physiological patterns throughout different condition during one testing session''* (Marwitz and Stemmler, 1998). Its goal is to identify the factors influencing the constancy in which a same situation induces the same physiological response in a subject. The IRS therefore refers to the stability of the psychophysiological relation (equation 1) for a given subject, and can explain in part why user-dependent recognition models have better results. Within the IRS framework, the specificity of the physiological reactions depends on the interaction of three components.

1. The **biological** component represents the subject's constitutional proprieties such as his/her morphology and his/her biochemical attributes (e.g. hypertension or glandular reactivity). This component is very stable and characterizes a great part of individual differences.

2. The **situational** factors are related to physiological responses according to many dimensions such as the familiarity of the situation, the range of possible reactions or the different situational constraints.

3. The **psychological** component explains how emotional reactions of a subject facing a situation are mediated by many psychological and evaluation factors such as personality, general attitude, cognitive styles and personal life experience.

From a pragmatic standpoint, obtaining information on biological factors is either intrusive or simply arduous to implement. For example, the measurement of the cortisol concentration, albeit correlated with different emotional responses (Nejtek, 2002), requires the sampling of saliva in the participants' mouth. Most works on ASP therefore address the biological component by using baselining methods. In this line of research, Johannes and Gaillard (2014) developed an approach based on cluster analysis that enable a better comparison of physiological signals between groups of subjects.

Addressing the situational component would require real-time information on the current context, and therefore would limit the general applicability of a recognition approach. Studies interested to this aspect of the relation are still too embryonic and do not permit the elaboration of useful and implementable conclusions in a machine learning context.

We therefore chose, as a first step, to work on the psychological component. From a pragmatic point of view, the justification of the integration of personality parameters stands on the fact that they are easy to collect, via questionnaires, and produce numerical data according to multiple dimensions easily modeled. The IRS states that for the same situation, a similarity of perception leads to a greater similarity in physiological reactions (Stemmler, 1997). As one’s personality is strongly related the way he or she evaluate a situation, we choose to first model psychological idiosyncrasies using personality traits. The literature already contains some results pointing in the same direction. For instance, van den Broek et al., (2009b) note that the relation between cardiac activity and emotional arousal is influenced by the extraversion personality trait. Crider (2008) reports many studies showing that electrodermal lability is linked to the subjects’ expressivity and disposition (antagonist or agreeableness). In a more general manner, a meta-analysis done by Myrtek (1998) presents correlations between 34 physiological variables and certain personality traits. The effect size of these correlations are ranging from small (r < |0.10|) to moderate (r < |0.30|).

4 EXPERIMENT

An experiment will be conducted to validate the proposed approach. Based on the Circumplex Model of Affect (Russell, 1980), users’ emotions will be modeled using the two psychological constructs of valence and arousal. Valence is used to contrast states of pleasure (e.g. happy) and displeasure (e.g. angry), and arousal to contrast states of low arousal (e.g. calm) and high arousal (e.g. surprise). Different levels of emotional valence and arousal will be induced using standardized images from the International Affective Picture System (IAPS) (Lang et al., 2008) (see Figure 2 for examples).

Figure 2: IAPS images (2352, 1304).

The recorded physiological signals will consist of electrodermal activity, cardiovascular activity, respiration, pupil diameter, and electroencephalographic activity. Personality will be assessed using the HEXACO Personality Inventory (Lee and Ashton, 2004). In line with the trait theory of personality, the HEXACO-PI defines six personality factors: Honesty-Humility, Emotionality, Extraversion, Agreeableness, Conscientiousness, and Openness to Experience. Analyses will consist in 1) testing if personality factors can act as moderator variables between each physiological feature and emotional target, and 2) assessing the improvement in accuracy brought by adding personality variables to a regular physiological prediction model. The latter will be implemented by instantiating the idiosyncratic parameters of equation 3 with the HEXACO personality factors (e.g. I_1= Openness, I_2= Extraversion).

5 CONCLUSIONS

In this paper, we proposed an approach to address the “genericity vs generalizability” dilemma at the hearth of the physiological emotion recognition problem in ASP. Our approach is based on the modeling of the idiosyncratic factors that underlie user-dependent recognition models’ higher accuracy. As a first exemplification, we described how personality traits can be used to improve the accuracy of user-independent emotion recognition models.

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