EEG-based Valence Recognition: What do we Know About the influence of Individual Specificity?

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***Abstract* — The fact that training classification algorithms in a within-subject design is inferior to training on between subject data is discussed for an electrophysiological data set. Event-related potentials were recorded from 18 subjects, emotionally stimulated by a series of 18 negative, 18 positive and 18 neutral pictures of the International Affective Picture System. In addition to traditional averaging and group comparison of event related potentials, electroencephalographical data have been intra- and inter-individually classified using a Support Vector Machine for emotional conditions. Support vector machine classifications based upon intraindividual data showed significantly higher classification rates [F(19.498),p<.001] than global ones. An effect size was calculated (d = 1.47) and the origin of this effect is discussed within the context of individual response specificities. This study clearly shows that classification accuracy can be boosted by using individual specific settings.**

Keywords - Human-Computer Interaction; Emotion recognition; Affective Computing; EEG; classification;

I. INTRODUCTION

Human life is increasingly influenced by complex information technology. Some years ago it was clear for a given user whether and how he interacted with a technical system. Today and in the future people will interact with various elements of this information technology to a far greater extent and in very heterogeneous ways. Ambient Intelligence for example, will be able to assist users smartly while preserving security and privacy [1]. Also, systems must automatically adapt to different communication modalities and the cognitive, emotional and motivational needs of users. Conceptualization of user-friendly features (usability) must go beyond traditional improvement of dialogs and develop empathic machines [2]. Particularly, methods are required, which allow one to use features and expressions of a user's emotional behavior for functional features and interaction design. Psychobiological parameters of the peripheral (PNS) and central nervous systems (CNS) are a continuously available source of emotion indicators. Using psychobiological measurements, predictions are more reliable as they show a decreased amount of reactance compared to the assessment via questionnaire or rating.

A. Individual data analysis

The concept of individuality and the associated specificities is nothing new in psychological research. Dealing with these circumstances in technical context means that one can calculate formulas or train classifiers and achieve very good results, but if the application on a single person is tried, classification rates are not ideal. This is especially problematic in an affective context, where things are quite fuzzy. Therefore, we tried to address this phenomenon and discuss the effect.

B. Individual psychobiological classifications

The question is whether there are specific psychobiological emotion patterns that can be assigned to certain emotional states? In past decades, several studies have been done searching for corresponding emotion patterns by means of regression analysis and analysis of variance, and demonstrated differences between subjects (interindividually) [3] [4]. In these psychobiological studies, patterns can be found that differentiate along emotional states: heart-rate variability (HRV) [5], skin conductance level (SCL) [5] or the late positive potential (LPP) [6] [7] for example. The present study shows, when interindividual and within subjects (intraindividually) determined psychobiological patterns are compared, the intraindividual approach shows superior results in classifying emotional states compared to the interindividual (global) one. We statistically tested (by using the effect size) the hypothesis that classification based upon intraindividual variance of the psychobiological reaction [4] shows more accurate results of emotion classification compared to classification based on interindividual variance. The influence of individuality on emotional experience is well known [8] [9], but so far, does

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not have a big impact on computer based emotion recognition.

Kim and Andre [5], for instance, argue that emotional experience is a construct of cognitive processes, physiological arousal, motivational tendencies, behavioral reactions and subjective feelings. They further report that physiological activity is not an independent variable, but rather reflects experienced emotional states with consistent correlates. We support this view and additionally believe that variance caused by the subjective character of the emotional experience can be used to achieve a more precise classification. To demonstrate this effect, we used very reliable stimulus material - the International Affective Picture System (IAPS) [10]. This stimulation material is described very well in its ability to induce emotions as well as to evoke CNS activity. Visual stimuli are often used in emotional psychobiology. Many studies have proven the IAPS-stimuli [3] [6] [7] to be a valid tool for controlled induction of emotion.

C. Analyzing central nervous responses

Apart from imaging methods, the electroencephalogram (EEG) is designed for the operationalization of the activity of the central nervous system. EEG is the method of choice for processing emotional stimuli, particularly when processing of emotional information takes place in a rapid temporal state on a scale of seconds [6]. As Schupp and colleagues showed, the time window between 350-750 ms after stimulus onset is profoundly relevant for processing of emotional pleasure. This CNS activity is called late positive potential (LPP) due to its relatively positive change in potential and it’s delayed (as far as EEGs go) onset [11]. LPP differentiates CNS processing of negative, neutral and positive visual emotional stimuli in a characteristic manner [6] [7].

D. Aims of this study

The aim of the present study is to determine the affective state post hoc via EEG-analysis by means of mathematical classification algorithms. The influence of individual variances on classification rates is quantified giving their effect size. Support Vector Machines (SVM) are used as classification method. SVMs transform the underlying data set into a higher dimensional space, in which a complex geometric separation plane is then drawn. This separation remains even after the subsequent transformation back to "normal" space [12]. Furthermore, this study intends to demonstrate statistically – with p-level and effect size [12] - that a classification approach, in which the SVM is trained with all data sets of all available subjects is inferior to training with individual data.

E. Article structure

In the following subsections, experimental conditions are described, followed by an overview of the classification procedure. Afterwards, results are presented for a) statistical analysis of preprocessed EEG data and b) comparison of two classification approaches, optimized using individual- and global fitted parameter settings. Finally, in the discussion part, individual specific influences on classification rates are discussed.

II. Methods

In this subsection, data assessment and the experimental setup will be described.

A. Subjects

18 (9 female) subjects (age range 18-30) were involved in the study. All subjects were right-handed, healthy, with no psychiatric history and had normal or corrected vision. The study participants received 15 euro remuneration. Subjects were informed about the content and procedure of the study. Following the respective briefing, which was conducted according to the criteria of the Ethics Committee of the Medical Faculty of the University of Ulm, the individual participants signed a written consent form concerning their participation in the study. The present study was classified as ethically unobjectionable (sfb ethics vote no. 245/08).

B. Experimental conditions

The subjects were instructed by the experimenter, about the course of events during the experiment, relevant tasks and the rating procedure using the Self-Assessment Manikin (SAM) [13]. The experiment took place in a darkened room within the Emotion Lab at the University of Ulm (Germany).

Psychobiological parameters were measured using sensors with a MindMedia NeXus-32 amplifier (http://www.mindmedia.nl) on 19 EEG and two EOG (horizontal, vertical) channels. EEG was recorded from 19 sites according to the 10/20 system [14] using an Easycap. Ag/AgCl electrodes were placed at FP1, FP2, AFz, F3, F5, F7, F6, Fz, C3, C5, Cz, FCz, P3, P5, Pz, O1, O2, T7 and T8. The linked mastoid (A1, A2) served as a reference. Data were digitized at a sampling rate of 256 Hz. Subjects were instructed to autonomous start the experiment with a mouse click as soon as the researcher left the room. After completing the experiment, subjects were asked to fill out some questionnaires about their personal constitution (NEO-FFI, 16 PF-R).

C. Experimental design

During the experiment, a set of selected images from the International Affective Picture System [10] was presented on a 21” CRT display at a distance of approximately 50 cm from the subject. Eighteen negative, eighteen positive and eighteen neutral pictures (54 in total) were presented in random order. Each image was presented for 6 seconds, followed by a variable jitter between 6 and 12 seconds. This served to prevent expectations. The individual impression of the subject was captured directly after each picture using the SAM [13]. Stimuli were presented using custom written software [15]. The same software was used for data acquisition.

D. EEG Preprocessing

Because of typical characteristics of an electrophysiological channel, the EEG signal recorded at the skull must be significantly amplified. This makes the analysis of the overall signal more difficult. The amplifier not only amplifies the desired psychobiological signals but also the background noise (mains hum, etc.). EEG signals can easily be corrupted and biased by applying inappropriate preprocessing, which has to be performed carefully for this reason. Therefore, we used the EEGLAB toolbox [16] developed for MATLAB.

First, the recorded data were imported and visualized by EEGLAB. The EEG signal was visually screened for artifacts. Whenever there was an artifact of more than 100mV in amplitude, the entire trial was excluded from further analyses. Subsequently, the EEG-signal was corrected for vertical and horizontal eye movement artifacts as described previously [17]. Only artifact-free trials with congruent subjective and normative categorizations of the pictures were included. Overall, 6.4% of all data were excluded from further investigation due to artifacts. To extract the EEG frequency range relevant for this study, data were band-pass filtered. The lower threshold of the filter was set to 0.1 Hz (high-pass) to eliminate linear trends in signal recording, while an upper threshold of 20 Hz (low-pass) cut off high-frequency noise. Preprocessed data were epoched in a further step – this means, separated by the stimulus category and edited to represent a time window of one second pre-stimulus to 6 seconds post-stimulus. In an averaging procedure data of the individual images of the respective categories were averaged across all subjects. Results of the averaging procedure are shown in Fig. 2. Statistical analysis of EEG data was carried out with SPSS 13. A t-test was used to compare the conditions of positive, negative and neutral conditions. The mean value of 350-750 ms after stimulus onset was used as a basis for statistical analysis.

E. Classification procedure

For classification of different psychobiological affective states we chose SVMs, as they have been proven to be very effective before [18] [19] [20], and to maintain enough flexibility with regard to their main parameter optimization (as discussed below) [21]. The goal of a SVM is to develop a predictive model from a given training data set x, so that respective training sets x_i and their associated labels y_i can be applied to an unlabeled test set in order to assign the test set to a particular class. In this case the SVM [22] aims to find an optimal solution for the following problem: minimize with respect to:

$$\mathrm{w}, \mathrm{b}, \xi: \frac{1}{2}\mathrm{w}^{\mathrm{T}}\mathrm{w} + \mathrm{C}\sum_{\mathrm{i}=1}^{\mathrm{m}} \xi_{\mathrm{i}} \quad (1)$$

So that the following constraint applies:

$$\mathrm{y_i}(\mathrm{w}^{\mathrm{T}}\phi(\mathrm{x_i}) + \mathrm{b}) \geq 1 - \xi_{\mathrm{i}}, \forall\, 1 \leq \mathrm{i} \leq \mathrm{m}, \xi_{\mathrm{i}} \geq 0 \quad (2)$$

By means of a kernel function :

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \quad (3)$$

the training sets x_i are transformed to a higher dimensional space, in which the SVM finds a separating hyperplane with maximum width. In the present case the Gaussian kernel was used

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0 \quad (4)$$

because it is able to handle non-linear dependencies between class labels and input attributes. Furthermore, the Gaussian kernel has the advantage that the complexity of the model is not influenced by too many parameters, but is only limited to two main parameters (C;γ, C>0), which enter into the above equation as a penalty parameter for the error term in (1).

For more details, the reader may refer to [12]. In the present study the classification was applied on the LPP using SVM. The time window for the LPP was ranging from 350-750 ms after stimulus onset [6]. Furthermore, the results of [7] served as a guide, as they show that, among others, the data of the EEG channel Fz are particularly effective in separating the three affective states. After the abovementioned preprocessing of EEG data from the Fz channel and subsequent epoching of all data of all subjects within the mentioned time window, every epoch was baseline corrected with a time segment of 350-400 ms after stimulus onset in order to make them more comparable. This step should create a distribution of the values around the baseline. The remaining data resulted in a 89 samples array (350ms measured at 250Hz). Finally the epochs were labeled according to the pleasure information (positive, negative or neutral). Thus, for every subject remained a data set with 54 epochs of 90 values each (89 time samples - corresponds to 89 features + 1 label attribute). No further features were added.

The SVM was developed as a binary classifier, but since this work intends to differentiate three states (negative, positive and neutral), the use of the LIBSVM learner developed by Chang and Lin was utilized, since it extends the principle of the traditional SVM and is able to differentiate multiple classes [23]. To obtain the influence of individuality on affective computing, optimal SVM parameters a systematic grid search was performed for C and γ with concluding leave-one-out cross-validation. Individual pairs of C- and –γ values are taken, plugged into the SVM and their classification accuracy is calculated using the leave-one-out cross-validation. After explorative testing of all combinations, the pair with the highest accuracy was finally selected as the optimal parameter set.

When choosing the parameter values, we followed the procedure of Hsu, Chang and Lin. [21], who recommend exponentially growing sequences for C and γ. In the first processing step, all steps of the classification procedure were carried out with the combined data set of all subjects (global), and the corresponding optimal parameter pair (C_{global} and γ_{global}) was determined (see Classification results). In a further processing step, the parameters C_{global} and γ_{global} of the SVM already identified by means of the global sample were applied to the data sets of the individuals (individual). The results are shown in Fig. 2. In an exploratory study, a parameter optimization on an individual level ($C_{individual}$ and $\gamma_{individual}$) was also performed, and the results of this optimization are also shown in Fig. 2. All classification experiments were performed on a laptop using the high-performance data mining software RapidMiner.

F. *Calculating effect sizes*

Effect sizes [24] were calculated for comparison of individual vs. interindividual classifiers using (5):

$$D = \frac{|\mu 1 - \mu 2|}{\sigma} \qquad (5)$$

III. RESULTS

In this subsection, results are shown of a) preprocessed data and b) the classification procedure.

A. *EEG Preprocessing*

Fig. 1 shows the evolution of the grand averages (grand average across all subjects) of the three conditions.

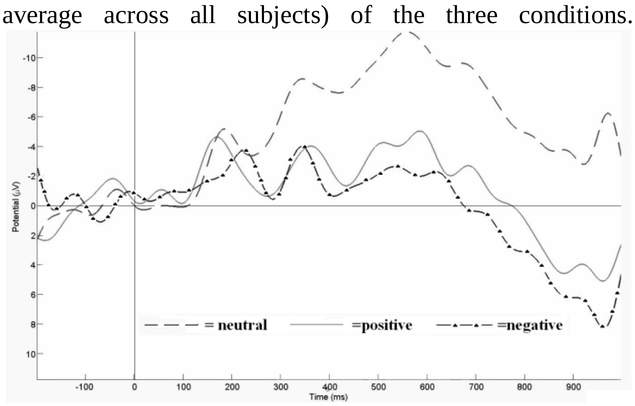

Figure 1. Grand averages of the evoked potentials on Fz for the three different conditions neutral(- - -), positive(—) and negative(-•-•-).

Further statistical analyses illustrated significant differences for the neutral versus negative and neutral versus positive conditions. A t-test for negative versus positive did not show any significant differences in the time frame of interest. Results of the Tukeys test for Fz electrode showed a significant difference for positive vs. neutral [t(11.4) = 3.59, p< 0.01] and negative vs. neutral [t(11.4) = 3.25, p < .05]. No significant differences were found for the conditions negative vs. positive [t(11.4) = 0.45, p = 0.661].

B. *Classification results*

Using the obtained optimal parameters C_{global} (= 2^{15}) and γ_{global} (=2^{-11}), the classification across all subjects (global) using leave-one-out cross-validation, resulted in an accuracy (relative number of correctly classified epochs) of 38.77%. The outcome of using global optimal parameters for calculating the detection rate at the individual level is shown in Fig. 2 for the respective subjects. However, if one calculates the optimal parameters specifically for each individual and uses them for classification, classification rate for each individual increases significantly.

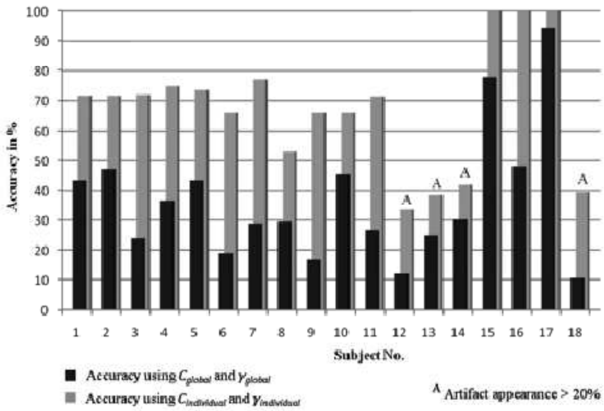

Figure 2. Comparison of classification rates with global and individually determined optimal parameters: classification rates with globally determined optimal parameters applied to each individual (black bars); classification rates with optimal parameters calculated separately for each individual (gray bars) term in traditional approaches. The improvement of the classification demonstrated here is based on the use of intracellular variance of CNS activity.

IV. DISCUSSION

Although statistical analysis was not able to show a difference between the classes positive and negative, classification rates were mostly above chance level.

A. *Conclusion of aims and scopes*

Objectives of this study were a) to classify emotional categories positive, neutral and negative using EEG signals and b) to demonstrate the influence of individual specificities on affective computing. Classification of the respective categories was performed with SVMs for each individual subject. In contrast to state of the art classification studies [6], this study used only filtered EEG data without any additional feature extraction. We did not use any special feature extraction due to the research question of individual differences and their impact on classification. Using pre-defined settings for detecting emotions (a global approach), some accuracy gets lost compared to use of a special trained classification (individual approach) process. This loss of accuracy may have several origins. On the one side, there is the accuracy of the classifier itself, which is more specified to unique patterns of an individual when it is trained only on responses of this particular person. On the other side there are the influences of the person itself, of their body and mind. These influences are known as individual specificities [9] and shall be discussed in the following subsection.

Using this knowledge of the origin of the variance caused by individual specificities, a model can be found, which provides more accuracy in the prediction of the emotional state than it would be possible by using further and further improved predefined settings.

B. General discussion

Using global determined optimal parameters for classification, detection rates that are not much higher than the mathematically random chance rates of 33.33% were calculated. If one determines the optimal parameters specifically for each individual, detection rates of over 40% up to 100% are possible (Fig. 2). This improvement is statistically significant [F(19.498), p< .001] with an effect size of d=1.47. Despite of the obtained individual, optimal parameters, there can be no question of overfitting. It is not, due to the fact that in the majority of data, an influence of variance caused by false true detection can be seen. The exceptions, which show a classification rate of 100% are owed to an extraordinary good physiological response of the subjects.

If one wants to deduce emotions of a person from their psychobiological reactions, it is necessary to keep the individual patterns, with which that person responds to emotional stimuli, in mind. This information would not be needed if all people would react equally to emotional stimuli. Since this is not the case, the individual variance of the psychobiological reaction enters into the error term. The theoretical starting point of this approach goes back to Lacey and colleagues, who were the first to empirically research the concept of response specificity (RS) [25]. The concept of RS is based on the assumption that variance of psychobiological reactions is due to situational, individual and motivational influences [26]. According to Lacey there are two types of individual response specificities (IRS) – intra stressor specificity, which can be observed in moments of stressful stimulation like showing a picture of a snake to a woman who is sensitive for this kind of fear.

The second concept is Symptom-stereotypy, which is characterized by the form of the maximal physiological response to a stimulus. The fact, that these responses are stable within the individual user is of great interest for interpretation of the physiological signal by a technical system. RS and especially IRS have been shown to have an impact on psychobiological empirically by Marwitz and Stemmler [27]. In the context of the results shown in this study, this means that there are response patterns to emotional stimuli, which are user-specific and therefore help to increase classification accuracy within the individual subject. If it is tried to generalize these findings to a between subject design, the classifier is over-fitted and prediction accuracy is decreasing, which would not be the case, if everyone would be responding in the same way. Using this knowledge, one can think of a sort of calibration technique, which supports the classifier to find a unique setting for a unique user.

Stemmler and Wacker [9] showed in their experiments that individual variance can be found in both the central and the peripheral nervous system. Therefore, the results of this study should not only be of interest for EEG analysis, but also for peripheral channels such as heart rate or skin conductance. But there are other sources of variance, too. Gender for example is known to have an influence on the shape of an ERP signal [28]. And there is even more, age, or the state of physical- and mental-health. All these factors are confounding the signal of one particular person and therefore decrease the accuracy of a classifier system.

As far as we know, the effect of individual variance is well known but the strength of the effect, which is of great interest for technical use, has not been quantified yet. Therefore we calculated the effect size, which is a much more reliable predictor for comparing these conditions than a simple correlation could be [24]. In the related literature, classifications using EEG data are quiet common, Schaaff & Schultz [29] for example were also using SVMs for the classification of EEG-data recorded by an EEG-Headband to recognize emotions for a humanoid robot the recognition-rate of 47,11% was achieved by a separated training and classification for each subject (N=5). If a relatively small group-size is used, the chance of measuring a homogenous group-effect is quite high. To get a more representative sample, we used a larger group consisting of both genders at heterogeneous age. In addition we used an Easy-cap, which is standard in EEG-research and therefore very reliable. Using these setting, we found the effect reported above, which plays an important role in the variance of the psychophysiological signal. This leads to several new questions for further research. According to the approach of individual specificities, one can try to quantify the different variances-sources and separate the error term in an individual manner, which will be more reliable than training on a steadily changing signal. This is economical as well. Due to the change of these individual factors, the training of the classifier will have to be done several times again, if the accuracy should not drop. But the more variance is solved in terms of known individual factors, the less is changing over time and situations.

We suggest that there has to be some sort of calibration, where the variance, caused by individual specificities can be identified and therefore gets solved. In general, it is likely that the classification rate in this study could have been improved by using an increased number of features; for example by adding means, variances or amplitudes and latencies of certain peaks, etc. see [20] for a detailed overview. In contrast to other studies [4] [5] [6] [8], further optimization of the classification rate was not the objective of this study. These sorts of techniques can be used additionally to explain the variance of the signal. What should be shown in this study is that there is a big effect, which has not been used yet that provides the opportunity to extract a more stable and more precise prediction of the affective state of a user. In future work, we will try to identify factors that explain the individual variance in a stable way. Therefore, a sample has to be chosen, which is big enough and heterogenic enough to vary the most common ways of individual specificities in a controlled paradigm.

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