ENHANCED METHOD FOR ROBUST MOOD EXTRACTION FROM SKIN CONDUCTANCE

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Abstract: One of the key challenges in affective computing is the interpretation of physiological signals into affect. Mood, as a subclass of affect, is known to be reflected in skin conductance. While most reports concern strictly controlled laboratory settings, daily life situations pose more challenges in interpreting physiology because more bodily and cognitive processes that influence skin conductivity are involved; for example temperature regulation or physical and mental activity. Existing techniques to reduce the effects of these processes in order to extract mood from skin conductance are rather crude and leave room for improvement. We introduce a more sophisticated method based on skin conductance response subtraction that provides better resemblance with mood. Validation of our method, using comparison with two alternative methods, shows our method excels in differentiation between positive and negative moods from skin conductance. Our method thereby enhances mood extraction from skin conductance, thus improving robustness of mood measurements.

1 INTRODUCTION

The role of technologies in our daily life is changing rapidly. It is expected that technologies more and more help us to balance our mind and body state as well. The importance of our mood is also increasingly recognized namely, being in a positive mood has the advantage to increase, among others, optimistic feelings to dominate our cognitive flexibility, problem solving capabilities (Lewis & Haviland-Jones, 2000), as well as our health and longevity (Salovey et al., 2000; Pressman & Cohen, 2005). Therefore it will not take very long before technologies that measure and that react to the affective state of the user will appear, e.g., a music player that plays music that suits or directs the mood state of the user (Janssen et al., 2009; Schroeder et al., 2008).

Mood is seen as our baseline body state, it is a tonic state which varies over minutes to days (Thayer, 1996). Changes in mood are accompanied by changes in our skeletal-muscular system (Cacioppo, 2000) as well as in our autonomic nervous system (ANS), reflected in e.g., skin conductance (SC; Van der Zwaag & Westerink, 2009). The use of SC in applications is promising because it can be unobtrusively and easily implemented in our daily life habits (Westerink et al., 2009).

SC is, besides mood, also affected by several other influences, among which physical and mental activity, environmental temperature, and emotions. In this paper we present a method to reduce the influence of these changes in SC that are other than mood, in order to obtain a signal that better reflects mood. This method is based on the fact that changes in mood are gradual and tonic, whereas the other aspects mentioned that influence SC have a phasic character; they are short and intense. In sum, our method is designed to remove the phasic effects in order to obtain a more resembling mood signal.

In mood research the ground truth available consists of subjective reports or effects hypothesized by the researcher. In order to quantify the success of the mood extraction method that will be proposed in this paper, we have chosen for a validation with hypothesized effects, which have been verified with subjective reports.

The remainder of this paper starts with a description of the physiological signals in section 2, followed by a detailed description of the method in section 3. Section 4 describes the validation of our method and we end with a conclusion.

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2 SIGNAL EXPLORATION

The skin conductance signal roughly contains two types of information (Dawson et al., 2000; Boucsein, 1992). The tonic SC, usually referred to as Skin Conductance Level (SCL), shows gradual changes over time. Phasic SC manifests as high(er) frequency components superimposed on the tonic level. These phasic SC components, known as Skin Conductance Responses (SCRs), have a typical form as schematically depicted in Figure 1: After a latency period (of approximately 2 seconds after observation of a stimulus), the signal rises relatively quickly, reaches a local maximum and then slowly declines again.

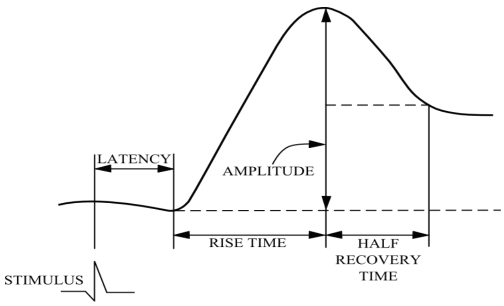

Figure 1: Graphical representation of a typical skin conductance response, taken from Dawson et al. (2000).

Most SCRs have a clear cause of their origin (Boucsein, 1992; Dawson, 2000), which can vary from an emotional event, physical activity or an internal thought. Moods, our psychological construct of interest, however, are long lasting affective states with no clear cause of their origin (Thayer, 1986); it is a tonic phenomenon like the skin conductance level SCL (apart from the SCRs). We therefore hypothesized, that removing SCRs from the SC signal would result in a SCL signal reflecting mood more precisely.

Although SCRs are well defined from onset to the moment of half recovery, their effect on a longer time span can be quite undeterministic: SCRs often decline until the onset level is reached, however they sometimes build on top of each other (humped SCRs) or the SC level does not decline to the onset level (i.e., there is a change in tonic level). Figure 2 shows an example trace of SC data in which the circles indicate the maxima of detected SCRs. The figure, for example, shows SCRs that decay to their onset level (e.g., around t=5), thereby only causing a phasic change; having no effect on the tonic level, as well as SCRs that cause a change in tonic level (e.g., the humped SCR with onset around t=1).

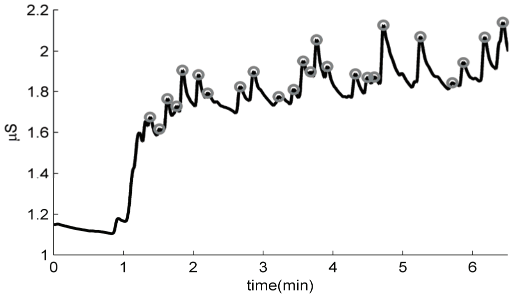

Figure 2: Example trace of SC data. The marks indicate the maxima of detected SCRs.

In this paper, we hypothesize the possibility to estimate the full phasic influence of an SCR by suitably extrapolating the well defined part of the SCR (from onset to half recovery time). All effects that remain after subtracting the SCRs from the signal (i.e., subtraction of the difference between the SCR and the SCR onset level), can then be considered as effects on the tonic level.

It should be clear that for this assumption the robust detection of SCRs is a necessity. Over time, multiple analysis techniques have been developed to extract the individual SCRs from an SC signal. A very basic technique compares the SC signal with a static threshold, after detrenting the signal, and fire in case of exceeding the threshold. More sophisticated methods, as the SCRGauge algorithm (Kohlisch, 1992), search for local maxima and use the notion of maximal curvature to find the onset of SCRs. The half recovery time value is searched for, and if not present, extrapolated.

3 ALGORITHM DESCRIPTION

Our method of processing the SC signal consists of three steps. 1) Each SCR needs to be detected, 2) for each SCR a model is fitted and 3) this model is subtracted from the original SC signal. The next three subsections describe these steps in more detail.

3.1 SCR Detection

The first step of the algorithm is to determine the individual Skin Conductance Responses (SCRs) reliably. For this we employ the SCRGauge method on top of which we build an extra layer that handles well those cases that SCRGauge indicates as doubtfully detected. In this extra layer, the half recovery time is extracted more reliably by linear extrapolation from the *first* occurring bending point (i.e., zero crossing of the second derivative) after the top of the SCR (in other words, use the tangent at the point of maximal decline). SCRGauge uses the same technique, however it extrapolates from the *last* bending point occurring before the signal rises again after the top of the SCR.

Besides that, the extra layer contains an improved indication of humped SCRs, i.e., SCRs that happen that soon after one another that they stack on top of each other, as can be seen in Figure 2 at t=1. We choose to combine the SCRs that have time wise overlap (considering rise time and half recovery time) and treat these humped SCRs as single large SCRs, by using the first onset, the maximal top and re-estimation of the half recovery time.

3.2 SCR Modelling

For each of the SCRs detected, a parameterized model is optimally fitted. This parameterized model should be a mathematical function that represents the shape of a typical SCR well. We used the sigmoid-exponential four-parameter SCR model as proposed by Lim et al. (1997):

$$y_m^i(t) = \begin{cases} 0 & t \leq T_i \\ \dfrac{g\ \exp[-(t-T_i)/c_d]}{\left(1+\left(\frac{t-T_i}{c_r}\right)^{-2}\right)^2} & t > T_i \end{cases} \qquad (1)$$

where the model of the i-th SCR (y_m^i) is characterized by four parameters: the onset time T_i, gain g (related but not identical to the SCR amplitude), and rise time and decay time constants c_r and c_d, respectively.

The optimal fit of the parameters can be determined by an error minimizing method, as for example minimization of the sum of squared error (also known as the method of least squares). This method minimizes the difference between the observed data (y_d) and the model (y_m):

$$\underset{c_r, c_d, \mu, \sigma}{\operatorname{argmin}} \sum_{t=T_i}^{T_i+\lambda} \left(y_d(t) - y_m(t-T_i)\right)^2 \qquad (2)$$

where T_i is the time of onset of the i-th SCR and λ specifies the length of the window that is taken into account for the comparison. To optimally fit the SCR, this length is defined dynamically to fit the SCR from onset to half recovery point, i.e., the window has a length equal to the sum of the rise time and the half recovery time (see Figure 1). In the cases that the half recovery time is extrapolated (during the extraction phase) the extrapolated signal can be used up to the half recovery time for determining the optimal fit.

There are several methods to solve the least squares problem, or more general, solve optimization problems; Lim et al. (1997) use the Marquardt-Levenberg method, we chose to use the Nelder-Mead Simplex Method (Lagarias et al., 1998), which is less susceptible for local minima (Miller, 2000). These optimization algorithms aim at finding an optimal set of (model) parameters such that a given measure is optimized (i.e., minimized or equivalently maximized), given an initial parameter setting. The averages found by Lim et al. proved to be sufficient as initialization of the parametric model.

3.3 Subtraction of SCRs

The parametric models (y_m^i) are used to subtract the SCRs from the SC signal (y) according to:

$$y^*(t) = y(t) - \sum_i y_m^i(t - T_i) \qquad (3)$$

For practical reasons, the modelled SCRs are taken into account from the onset time T_i, see equation (1), up to where their contribution is negligible. In only few occasions the optimization did not lead to a good fit of the model, characterized by a major overestimation of the tails of the SCRs. These cases are recognized by extraordinary parameter values and treated with extra care, i.e., the signal after subtraction is limited by the original SC signal, thereby ensuring the signal does not decay below the SCR onset value (for the duration of the SCR). Figure 3 shows an example trace of SC signal with projections of the modelled SCRs.

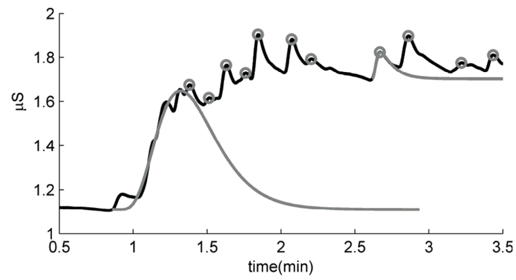

Figure 3: Overlay of two modelled SCRs (grey) on the original SC signal (black) for a ‘simple’ SCR (right) and humped SCR (left).

Figure 4 shows the residual signal after subtraction of the modelled SCRs as the dark grey line close to the black line. It can be seen that high frequency noise is introduced in the residual signal

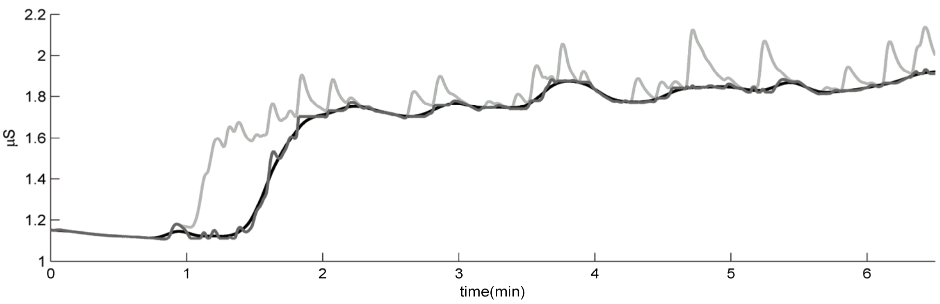

Figure 4: Overview of the original signal (light grey), and the residual signal before (dark grey) and after (black) filtering.

because of local misfits of the SCR models. We applied a small low-pass filter, 8 second moving average, afterwards in order to smooth the residual signal as displayed in Figure 4.

In the following, we will refer to the complete algorithm as SCR subtraction, whereas this sub-step of removing the SCRs will be referred to as subtraction of SCRs.

3.4 Alternative Techniques

In mood research alternative techniques have been applied also with the aim of obtaining a better mood signal from SC. To our knowledge, these alternative methods include (strict) low-pass filtering and interpolation of SCR onsets (Lykken & Venables, 1971).
Figure 5 shows an overview of their effects on an example trace of SC data.

We implemented the first method using a moving average filter with relatively large windows of 50 and 100 seconds. This method has as advantage that it does not rely on the detection of individual SCRs. It however has a strong tendency to overshoot the original signal.

The latter method highly depends on the correct detection of SCRs and moreover, the correct detection of humped SCRs. As can be seen in

Figure 5, especially the presence of small SCRs (close to larger SCRs) causes this method to relatively closely resemble the original SC signal.

3.5 Complexity

The methods mentioned above, can roughly be divided into two groups: those that rely on SCR detection and those that do not. The low-pass filtering methods fall into the last category and are clearly of linear complexity; each sample needs to be multiplied with a constant number of filter coefficients.

When SCR detection is involved, the complexity of the method depends on the algorithm used for SCR detection. SCRGauge uses searching strategies which can, in worst case scenario's, result in quadratic complexity (i.e., the number of comparisons per sample can be in the order of the total number of samples). In our implementation we, however, bounded the number of search steps by a constant maximum, thereby ensuring linear complexity of the SCR detection (note that the maximum number of steps is rarely reached in practice). Our method also incorporates SCR modelling, which uses an optimization algorithm. Also here, the number of iterations is bounded by a constant, therefore the complexity is in the order of the number of data samples taken into account for the model (e.g., comparable to λ in equation (2)), which we also bounded by a constant. Finally the subtraction of SCRs is also linear in the number of data samples.

In summary, all methods are of linear complexity. Where low pass filtering is least computational complex, our SCR subtraction algorithm requires more calculation steps. The time needed, on a standard working station, however, is still small enough to allow real time application. With little effort on a more efficient implementation, it should also run on, e.g., a mobile phone or pda.

4 VALIDATION

In order to validate the proposed method, we applied it to a dataset containing SC signals (van der Zwaag & Westerink, 2009). SC was recorded during two sessions where a positive or a negative mood was induced in 37 participants using music. Each session started with a habituation period of eight minutes in which the participants could relax, after which the participants were asked to pay attention to eight minutes of music presentation. To verify the state of

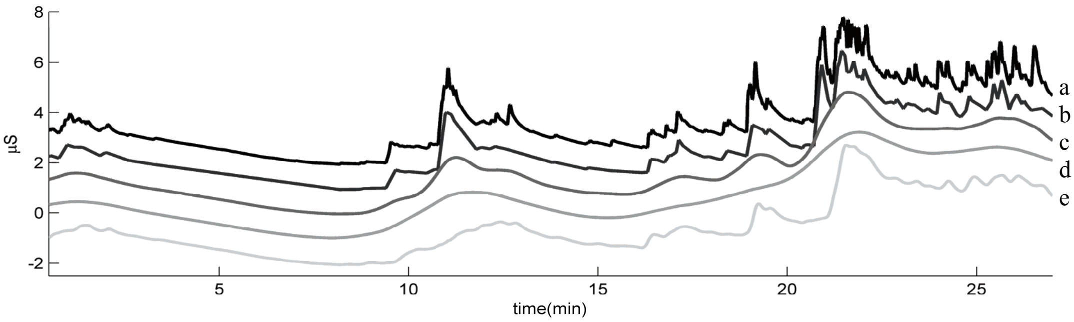

Figure 5: Comparison of (alternative) techniques, showing, from top to bottom, a) the original SC signal, b) interpolation of SCR onsets, low pass filtering (moving average), using a window of c) 50 and d) 100 seconds, and e) our method: SCR subtraction. In order to improve visibility, the latter four have been offset with -1 to -4 µS, respectively.

the participants, the UMACL mood inventory was presented after the habituation period and the mood induction (Matthews, 1990). Results show that the two moods were successfully induced. See Van der Zwaag & Westerink (2009) for detailed information on the design of the experiment and the data gathering.

We applied our SCR subtraction method as well as two alternative processing methods on the available dataset; the processed signal will be referred to as skin conductance level (SCL) and the three methods applied will be referred to as: Plain SC, Low-pass filtering, and SCR subtraction.

Successively, the means (in analogy to SCL-mean) were calculated for each minute of the habituation phase and the mood induction period. To compensate for individual differences in SCL, the features x, derived from SCL, were normalized for each participant per session using z-transformations:

$$x_i^* = \frac{x_i - \mu_x}{\sigma_x} \tag{4}$$

where feature instance x_i is transformed using the mean μ_x and standard deviation σ_x taken over the third till fifth minute of the habituation period, thereby serving as baseline period. Thereafter a repeated-measures ANOVA with the mood (positive / negative) and time (minute 1 till minute 8) was conducted on the data obtained from each method. Results solely show a main effect for mood for SCR subtraction; meaning that positive and negative moods can be distinguished in SCL in this method only (Plain SC: $F(1,34)=1.14$, $p=.294$, $\eta^2=.032$; Low-pass filtering: $F(1,34)=3.01$, $p=.092$, $\eta^2=.081$; SCR subtraction: $F(1,34)=5.69$, $p=.023$, $\eta^2=.143$). Post-hoc analyzes of our SCR subtraction method show that the positive and negative moods can be differentiated from the fourth minute of mood induction onwards.

As can be seen in Figure 6, the SCR subtraction method provides the smallest error bars of the three methods, indicating that the data is more consistent over participants. The effect sizes (η^2) are additionally larger in the SCR subtraction data then in the data of the other methods; implying the strength of the relation between mood and SCL is larger in the SCR subtraction method. The mood with time interaction in the SCR subtraction data show that the relation between mood and SCL increases over time (from $\eta^2=.008$ in the first minute to $\eta^2=.361$ in the eighth minute).

Please note that we did not apply any participant or data removal criterion, including outlier removal. Together with the large difference between positive and negative mood the SCR subtraction method shows (in Figure 6), this indicates that the inter-personal noise has been reduced significantly, implying that our method is robust to inter-personal differences in physiology.

To summarize, we can conclude that the SCR subtraction method is the only method where positive and negative moods can be fully discriminated from the SC. Treated with this method, the SC signal represents mood best and is more accurate than the Plain SC and the Low-pass filtering method.

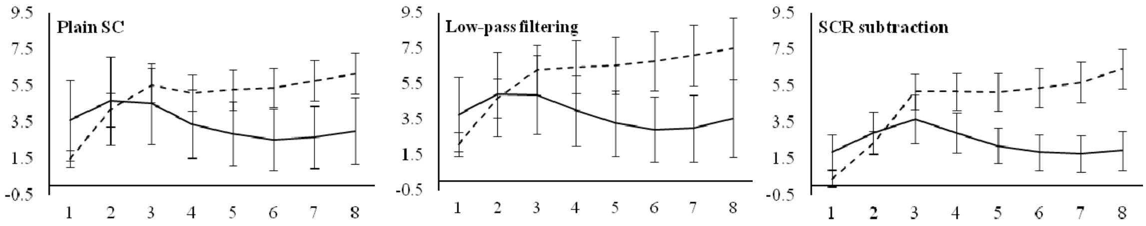

Figure 6: The three figures show the differentiation between moods by mean SCL (in normalized units (n.u.)) for the three methods discussed. The time in minutes during the mood induction is presented on the horizontal axis. The dotted (continuous) lines indicate the positive (negative) mood condition. Error bars indicate the standard error.

5 CONCLUSIONS

We propose a method to adjust the skin conductance signal in order to better reflect mood. It is based on the observation that SCRs, which frequently occur on top of the tonic SCL, correspond to event type stimuli that are not related to mood. The SCR subtraction method removes these phasic influences from the SC signal by subtracting the SCRs from the SC so that an estimate of the pure SCL signal remains. We validate the SCR subtraction method with SC data taken in a mood induction experiment. The results show that the SCR subtraction method outperforms the alternative SCL estimations. In fact, the SCR subtraction technique is the only method resulting in significant differences between the positive and negative moods.

Using the method we present, skin conductance can serve as a robust indicator for positive versus negative mood. Whenever someone's mood can be measured, steering one's mood, or creating awareness of one's mood, is only one step away. As mentioned in the introduction, the range of possible applications is very broad, including systems that help in making us feel better, and healthier.

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