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On Correlation Between Single-Trial ERP and GSR Responses: a Principal Component Regression Approach

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Abstract— **In this study we investigate the correlation between single-trial evoked brain responses and galvanic skin responses (GSR). The correlation between the two signals is examined by using a modified principal component regression based approach. A potential application of the study is to utilize the GSR measurements in a form of a prior information in the estimation of the brain potentials when only small number of trials is available.**

I. INTRODUCTION

Event related potentials (ERP) have been widely used for studying brain activity associated with higher mental functions. Investigation of the dynamic features of the event-related potentials, including the trial-to-trial variability of the responses requires an estimation of single potentials.

We have proposed subspace regularization based approaches for estimation of single-trial ERP responses [1], [2]. The proposed methods take advantage of the second order statistics of the measured data. In practice, to be able to have reasonable statistics it is necessarry to use dozens of responses. In some cases this can be problematic, for example when studying strong habituation like the orienting response. However, often some other signals such as galvanic skin response (GSR), also known as skin conductance response (SCR), are measured simultaneously with ERP measurements.

The galvanic skin response is a simple, useful and reproducible method of capturing the autonomic nerve response as a parameter of the sweat gland function [3]. Physically GSR is a change in the electrical properties of the skin in response to different kinds of stimuli. Any stimulus capable of an arousal effect can evoke the response and the amplitude of the response is more dependent on the surprise effect of the stimulus than on the physical stimulus strength. In measurements, changes in the voltage measured from the surface of the skin are recorded.

Previous studies have shown that the amplitude of the late positive components of ERP and GSR measurements correlate. In studies investigating the quality of the ERP showing habituation of the orieting response, like [4], [5], [6], it has been shown that the amplitude of the both signals decrease when GSR habituates. In this study we investigate the correlation between the single-trial responses using principal component regression (PCR) based approach.

II. METHODS

A. Measurements

Fifty-eight channel continuous EEG was recorded using modified 10-20 system electrode cap. The galvanic skin responses were recorded using Ag-AgCl electrodes affixed to the palm and dorsal side of the non-dominant hand. All signals were recorded with a NeuroScan^{TM} system by NeuroSoft Inc. Signals were filtered on-line with bandpass 0.3-50 Hz. The sampling frequency of the recording was 500 Hz but for the analysis EEG signals were resampled to 250 Hz and GSR signals to 31 Hz.

The auditory oddball paradigm was used for stimuli. It consisted of 85% of standard (800Hz), 15% of deviant (560Hz) and 10 unique novel tones delivered with an inter-stimulus-interval of 1s. All tones were delivered to right ear of subject at 55 dB above hearing level. The novel tones were human sounds randomly presented among standard and target stimuli. Subjects were advised not to pay attention to standard stimulus and to push a button when hearing a target stimulus. They were not informed about the novel tones. Time between consecutive novelties were random but at least 30 seconds.

B. Preprocessing of signals

After each novel stimulus epochs of 8 second GSR response and 1 second ERP from channel Cz were extracted for the analysis. As a preprocessing step the ERP signals were lowpass filtered using smoothness priors method [7]. The filtering was made using conservative value for regularization parameter, thus only removing the highest frequency components from the response. The filtering did not have any significant effect to the most dominant principal components. Aim of the filtering was just to ease the visual inspection of the responses. The GSR resposes were rescaled to have equal maximum amplitude with the ERP responses without affecting the habituation pattern of the GSR responses.

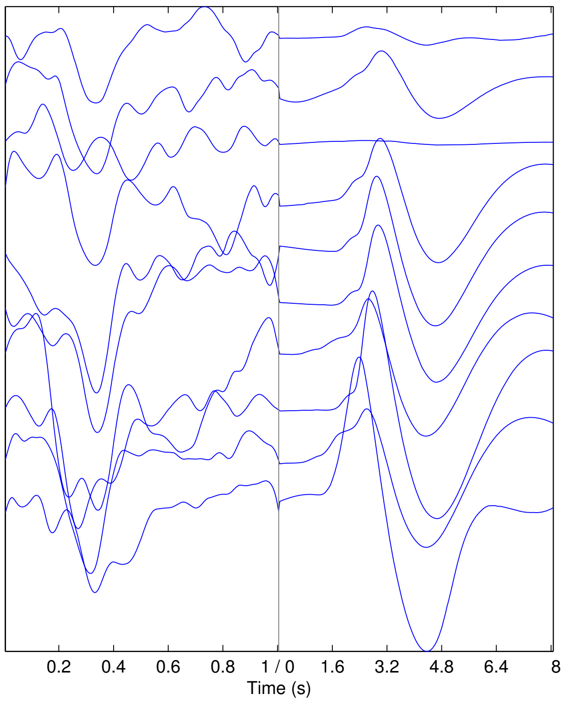

Fig. 1. Stacked measurements of the test person. For the visualization the matrix Z is transposed on the figure, thus on the left side are ERP responses on channel Cz and on the right side GSR responses. Ten repetitions of the novel stimulus, the first response is at bottom and the last at top. Scale of the y-axes is arbitrary.

C. Formulation of PCR

Principal component regression (PCR) is a multivariate statistical procedure, where the vector containing the measured signal is presented as a weighted sum of orthogonal basis vectors [8]. The central idea in PCA is to reduce the dimensionality of the data set, while retaining as much as possible of the information in the original data.

For the analysis the ERP and GSR responses were stacked together to form the data matrix. We use here the following notation for the measurements. The sampled potentials after j'th stimulus are denoted with a length $2T$ column vector

$$z^{(j)} = \begin{pmatrix} z^{(j)}_{ERP}(1) \\ \vdots \\ z^{(j)}_{ERP}(T) \\ z^{(j)}_{GSR}(1) \\ \vdots \\ z^{(j)}_{GSR}(T) \end{pmatrix}. \tag{1}$$

If we have N epochs, we can form a $2T \times N$ measurement matrix $Z = (z^{(1)} \ldots z^{(N)})$. The top part of augmented Z, containing only the data of ERP channel, is denoted with Z_{ERP} and the bottom part containing the GSR responses is denoted with Z_{GSR}. Stacked measurements Z are shown in the Fig. 1 for the test person I. In the figure the first response is at the bottom and the tenth response is at the top of the axes.

As an observation model for the measurements we use the so-called additive noise model

$$z^{(j)} = s^{(j)} + v^{(j)} \tag{2}$$

where $s^{(j)}$ is the response signal corresponding to j'th stimulus and $v^{(j)}$ is measurement noise. The measurement noise is assumed to be a stationary zero mean process. If we make N measurements, the response signals $s^{(j)}$ will span a vector space $\mathcal{S}$, which will be at most of $\min\{N, 2T\}$ dimensions. Using the measurement matrix Z the observation model (2) can be written in the form

$$Z = H\theta + v \tag{3}$$

where $H = (\psi^{(1)}, \ldots, \psi^{(N)})$, $\theta = (\theta^{(1)}, \ldots, \theta^{(N)})$ and $v = (v^{(1)}, \ldots, v^{(N)})$.

The critical point in the use of model (3) is the selection of basis vectors $\psi^{(i)}$. A variety of ways to select these basis vectors exist. For example a selection of trigonometric basis is the Fourier series approach. Here we will concentrate on a special case when the basis vectors are orthonormal to each other. This means that $H^T H = I$ and hence the ordinary least squares solution becomes

$$\hat{\theta}_{\text{LS}} = (H^T H)^{-1} H^T Z = H^T Z \tag{4}$$

Furthermore, the estimates for the observations can be written in the form

$$\hat{Z}_{\text{LS}} = H\hat{\theta}_{\text{LS}} = HH^T Z = \sum_{i=1}^{N} \psi^{(i)} c^{(i)} \tag{5}$$

where $c^{(i)} = \psi^{(i)^T} Z$. If the measurements Z are random, the coefficients $c^{(i)}$ are also random parameters. Hence we will require the coefficients $c^{(i)}$ to be uncorrelated and we can write

$$\begin{aligned} E\left\{cc^T\right\} &= E\left\{H^T Z Z^T H\right\} \\ &= H^T R_z H = \text{diag}\left(\lambda^{(1)}, \ldots, \lambda^{(N)}\right) \end{aligned} \tag{6}$$

This is an eigenproblem and the basis vectors are obtained as eigenvectors of the data correlation matrix $R_Z = \frac{1}{2T} Z Z^T$.

In the case that there is similarities in measured waveshapes, the dimension of the vector space $\mathcal{S}$ will be $K \leq N$ and measurements can be well approximated with some lower dimensional subspace of $\mathcal{S}$. We can thus express each measurement as linear combination

$$Z = H_{\mathcal{S}}\theta + v \tag{7}$$

where $H_{\mathcal{S}} = (\psi^{(1)}, \ldots, \psi^{(K)})$ is a $2T \times K$ matrix of basis vectors which span the K dimensional subspace of $\mathcal{S}$ and $\theta^{(j)} \in \mathbb{R}^K$ is a column vector of weights to j'th measurement.

The regression matrix $H_{\mathcal{S}}$ can also be divided similarly as Z into top ERP part denoted with $H_{\mathcal{S}(ERP)}$ and bottom GSR part denoted with $H_{\mathcal{S}(GSR)}$, i.e.

$$H_{\mathcal{S}} = (\psi_1, \ldots, \psi_K) = \begin{pmatrix} H_{\mathcal{S}(ERP)} \\ H_{\mathcal{S}(GSR)} \end{pmatrix}. \tag{8}$$

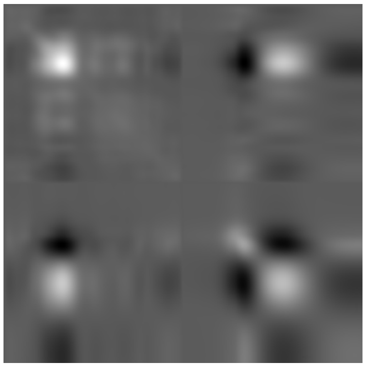

Fig. 2. Correlation matrix of the measurements shown in Fig. 1. Light areas show positive correlation and dark negative correlation.

The LS coefficients describing GSR responses can be solved from (4) as

$$\hat{\theta}_{GSR} = \left(H^T_{\mathcal{S}(GSR)} H_{\mathcal{S}(GSR)} \right)^{-1} H^T_{\mathcal{S}(GSR)} Z_{GSR}. \quad (9)$$

Although $H_{\mathcal{S}}$ is orthonormal and thus $H^T_{\mathcal{S}} H_{\mathcal{S}} = I$, the $H_{\mathcal{S}(GSR)}$ is not necessarry orthonormal and the inverse of $H^T_{\mathcal{S}(GSR)} H_{\mathcal{S}(GSR)}$ has to be calculated.

ERP responses can now be estimated according to (5) by using parameters estimated from GSR measurements

$$\hat{Z}_{ERP} = H_{\mathcal{S}(ERP)} \hat{\theta}_{GSR}. \quad (10)$$

D. Characteristics of PCR

Quantitatively the first basis vector is the best mean square fit of a single waveform to the entire set of measurements. The second basis vector is the best mean square fit to the residual from the fit of the first factor, with a constraint that it is orthogonal to the first basis vector etc. Hence by using eigenvectors $(\psi_1, \ldots, \psi_K)$ corresponding to largest eigenvalues $(\lambda_1, \ldots, \lambda_K)$ as basis, the best K dimensional approximation of measurements in the least squares sense is obtained.

When the correlation is calculated using the stacked measurements Z, the eigenvectors model also the correlation between the signals. Because principal component solution is a best fit of a set of orthogonal functions to the set of signals, the solution will depend upon the nature of signal set.

III. RESULTS

The data correlation matrix for the test person I is shown in the Fig. 2. By construction the correlation matrix contains four blocks. Diagonal blocks contain the autocorrelation matrices of the ERP and GSR measurements. The cross-correlation matrices are in top right and bottom left block. In the image, positive correlation is shown with light colors and negative correlation is represented in dark colors. We can see that there are some clear signs of correlation in the crosscorrelation blocks of the matrix around 300 ms stimulus onset.

The first six eigenvectors of data correlation matrix corresponding to the six largest eigenvalues are shown in the Fig. 3. Both ERP and GSR signal seem to be present in every eigenvector.

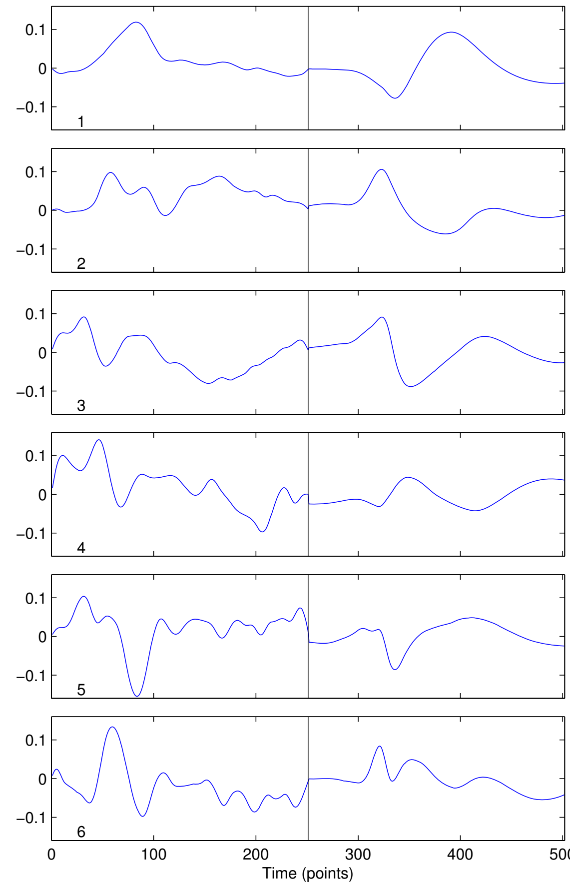

Fig. 3. Six eigenvectors of data correlation matrix corresponding the six largest magnitude eigenvalues.

One way to investigate the correlation between the GSR and ERP signals can be based on the eigenvectors of the correlation matrix of the stacked epochs. That is, to first estimate the fitting parameters based on the GSR data according to (9) and then use these parameters to obtain estimates for ERPs according to (10). The quality of the ERP estimates can reveal information about the relation between the two signals. In Fig. 4 is shown this kind of modified principal component regression fit for ERP responses of test person I. We used six eigenvectors in fitting. In the Fig. 5 is shown the same results for test person II.

For the test person I it can be observed to be around seven reasonably good estimates. The estimates for last three responses do not satisfactory describe the measurements. This is not suprising since the last three GSR responses are weak, as can be seen from the Fig. 1. For the test person II we also have seven good estimates. The estimates for responses 3,4 and 6 do not fit well to the data. Overall it seems that it is possible to estimate the ERP response with the commonly calculated eigenvectors and GSR optimised parameters reasonably well. This suggestes that there exists correlation between ERP and GSR responses.

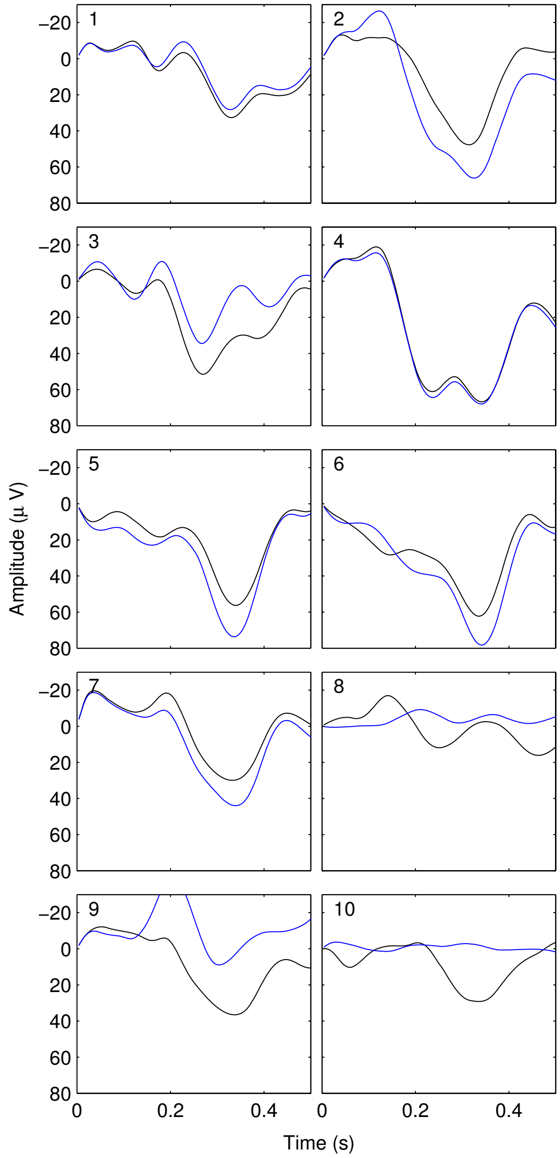

Fig. 4. ERP responses (black) and principal component regression of GSR measurement based estimates of ERPs (blue) for test person I.

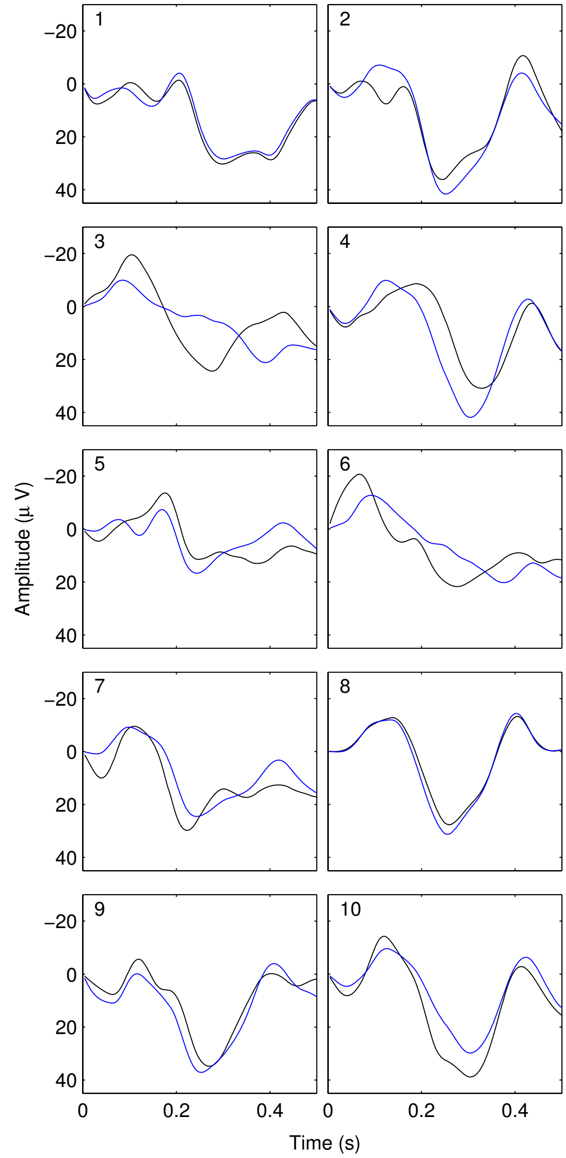

Fig. 5. ERP responses (black) and principal component regression of GSR measurement based estimates of ERPs (blue) for test person II.

IV. CONCLUSIONS AND FUTURE WORKS

In this study we investigated the correlation between evoked brain response and GSR. Our findings are in line with the previous works and we were able to estimate the P3 response reasonably well from GSR measurements.

Since the ERP and GSR responses seem to be correlated it should be investigated how the GSR responses can be utilized as a prior information in the single-trial estimation of ERP responses.

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