

PsPM: Psychophysiological Modelling

October 25, 2016

Version 3.1

incorporating SCRalyze

by the PsPM team¹:

Dominik R Bach, Giuseppe Castegnetti, Samuel Gerster,
Saurabh Khemka, Christoph Korn, Tobias Moser, Philipp
C Paulus, Matthias Staib, and collaborators

Contents

I	Background	6
1	What is psychophysiological modelling?	6
1.1	What is psychophysiology?	6
1.2	Operational analysis	6
1.3	Model-based analysis	6
2	Method comparison	7
3	General model structure	9
3.1	General	9
3.2	Peripheral models	9
3.3	Neural models	10
3.4	Model inversion	11
3.4.1	Hierarchical summary statistic approach	11
3.4.2	Probabilistic model inversion	11
3.4.3	General linear convolution model (GLM)	12
3.4.4	Non-linear model inversion	12

¹If you have comments on or error corrections to this documentation, please send them to the PsPM team or post them on: pspm.sourceforge.net

4	Skin conductance (SCR) models	12
4.1	General	12
4.2	Peripheral LTI model	13
4.2.1	Model evaluation	13
4.2.2	Skin Conductance Response Function (SCRF)	14
4.3	Neural model and model inversion	17
4.3.1	General Linear Model (GLM) for evoked SA	17
4.3.2	Non-linear model (DCM) for event-related SA	17
4.3.3	Non-linear model for tonic SA (spontaneous fluctuations, SF)	18
4.4	Data conditioning	19
4.4.1	Filtering	19
4.4.2	Normalisation	19
4.5	Implicit estimates of tonic sympathetic arousal	19
4.6	Comparison with other model-based methods for SCR	20
4.7	Recommendations	20
5	Heart Period (HP) Models	21
5.1	General	21
5.2	Peripheral and neural model	22
5.3	Model for event-related HPR	22
5.4	Model for fear-conditioned HPR	23
5.4.1	Adaptation to different SOAs	24
5.5	Data Conditioning	24
5.5.1	QRS detection	24
5.5.2	Interpolation and Filtering	25
5.6	Recommendations	25
6	Pupil size response (PSR) models	25
6.1	General	26
6.2	Model for pupil size changes elicited by (il)luminance changes	26
6.2.1	Model for steady-state pupil size	26
6.2.2	Model for pupil dilation/constriction	26
6.3	Model for pupil size changes elicited by fear conditioning	27
6.4	Data preconditioning	28
7	Respiratory response models	28
7.1	General	28
7.2	Peripheral and neural model	29
7.3	Models for evoked respiratory responses	29
7.4	Model for fear-conditioned RAR	30
7.5	Data Conditioning	30
7.5.1	Breathing cycle detection	30
7.5.2	Interpolation and Filtering	31
7.6	Recommendations	31

II	User Guide	31
8	Installation	32
9	General points	32
9.1	File types	32
9.2	Functions that create new data files	32
9.3	Functions that create or modify data channels in an existing file	33
10	Data preparation	33
10.1	Import	33
10.2	Trim	37
11	Data preprocessing	39
11.1	Preprocess heart data	39
11.2	ECG editor	41
11.3	Preprocess respiration data	45
11.4	Prepare illuminance GLM	46
11.5	Find valid fixations	48
11.6	Convert pupil data	50
11.7	Find startle sound onsets	50
12	First level	52
12.1	GLM (modality-independent options)	52
12.2	GLM for SCR	56
12.3	GLM for evoked HPR	57
12.4	GLM for fear-conditioned HPR	57
12.5	GLM for fear-conditioned PSR	58
12.6	GLM for evoked RAR	58
12.7	GLM for fear-conditioned RAR	59
12.8	GLM for evoked RPR	59
12.9	GLM for evoked RFRR	59
12.10	Non-Linear Model for SCR	60
12.11	SF models	63
12.12	Review First-Level Model (via Batch editor)	66
12.13	First-Level Model Review Manager (via GUI)	67
12.14	First-Level Contrasts (via Batch editor)	67
12.15	First level contrast manager (via GUI)	69
12.16	Export Statistics	69
13	Second level	70
13.1	Define Second-Level Model	70
13.2	Report Second-Level Results	71

14 Tools	72
14.1 Display Data	72
14.2 Data editor	72
14.3 Rename File	74
14.4 Split Sessions	74
14.5 Merge files	75
14.6 Artifact Removal	75
14.7 Downsample Data	76
14.8 Interpolate missing data	77
14.9 Extract segments	77
14.10 Segment mean	79
14.11 Extract event marker info	79
15 Troubleshooting and known problems	80
15.1 Path	80
15.2 Diagnostic graphics for non-linear model inversion	80
15.3 Export statistics into text format with tab delimiter	80
III Tutorial	80
16 GLM for SCR tutorial: Appraisal data	80
16.1 Import	81
16.2 Trim	82
16.3 First-Level	84
16.4 Review First-Level Model	86
16.5 First-Level Contrast Manager	90
16.6 Export Statistics	90
16.7 Adapting scripts for multiple participants and second-level analyses	90
17 Non-linear SCR tutorial: Delay fear conditioning data	90
17.1 Setup the Non-Linear Model	91
17.2 First-level Contrasts	95
17.3 Exporting statistics	95
18 Adapting scripts for multiple participants	96
18.1 Importing and trimming data	96
18.2 Inverting non-linear models	97
19 Second-level Contrast Manager	99
19.1 GLM	99
19.1.1 Define Second-Level Model	99
19.1.2 Report Second-Level Results	100
19.2 Non-linear models	100

<i>CONTENTS</i>	5
IV How to reference PsPM	102
V Release notes	104
20 PsPM Version 3.0	104
21 PsPM Version 3.0.1	106
22 PsPM Version 3.0.2	107
23 PsPM Version 3.1	107
VI Acknowledgements	108
VII References	109

Part I

Background

1 What is psychophysiological modelling?

1.1 What is psychophysiology?

The field of peripheral psychophysiology is concerned with the relationship between the mind (i.e. psychological processes) and the body (outside the brain). This relationship is bidirectional: the mind influences the body, but processes in the body are monitored by the mind via proprioception and interoception. Knowledge on this bidirectional relationship affords for instance examining more closely how psychological factors influence health, or how the interceptive abilities of an individual affect his psychological well-being.

A particular and very common application of psychophysiological knowledge is to measure processes in the body (sweating, heart activity, respiration, etc.) to assess processes in the mind. As an example, a person in a state of fear will sweat more. This knowledge enables us to measure skin conductance responses (SCR) and infer the psychological state of the person. Such inference can be made in various ways which are explained in the next paragraphs.

1.2 Operational analysis

Operational approaches seek to identify data features (“indices”) that closely follow a psychological state of interest. Operational data analysis algorithms extract these data features, to “index” central states. For example, to infer stimulus-evoked sympathetic arousal (SA) from skin conductance responses (SCR), one may filter the SCR data to reduce observation noise, define a response window after the stimulus, and define some criteria to detect peaks within this window. The amplitude of such peaks may then be taken as “index” of SA. The development of such indices is an important application of psychophysiology. Such indices are usually based on qualitative or semi-quantitative models of how the index relates to the psychological state of interest. Model-based analysis seeks to make these implicit models explicit (i.e. testable) in mathematical form - see [1] for a review.

1.3 Model-based analysis

Model-based approaches start with explicit, mathematical models that formulate how observed data are generated by psychological processes. For example, a model may formulate the relation between sympathetic arousal (SA) and skin conductance responses (SCR), $SA \mapsto SCR$, in mathematical form. This kind of model is often termed a “forward model”: it predicts a data time series (SCR) from a known psychological process (SA). Another term for this kind of model is “generative”, because it describes how a psychological process generates the data.

When we analyse experimental data, we are faced with the opposite situation: we know the observed data but not the central process, and seek to infer the central process from the data. In order to do so, one has to turn the forward model backwards, to arrive at the relation $SA \leftarrow SCR$. In statistics, this process is often termed "model inversion". It provides the most likely estimates of the central process, given the observed data and the model. Both conventional and model-based analysis aim to infer central process from observed data. The difference is that model-based methods use a stringent mathematical language and probabilistic model inversion to do so. Note that probabilistic models acknowledge the existence of noise in the data, and they do not seek to explain this noise with variation in psychological states. Hence, the criterion for the quality of a model-based method is not how well the model "fits the data", but how well it can recover the psychological variables of interest. In other words, the model should be able to fit the data but at the same time to ignore noise in the data.

2 Method comparison

How can we infer that one method of inferring a central state is better than another? Each method returns indices or estimates of the psychological state, but which ones are more precise? Usually we are interested in psychological variables that can not be measured directly. The solution we propose to evaluate a method is to experimentally create two psychological states that are known. We can then evaluate how well a method recovers these known states. In the simple example of fear conditioning, we could compute a paired t-test on the CS+/CS- difference in the estimates and assess the test statistic - the method that yields a higher t-value is more precise. But is it also significantly more precise than the other method? This can be assessed with a formal model comparison.

In our example, we can try to predict CS identity (CS+/CS-) from the model estimates. This means testing evidence for a model in which individual participants' CS+ and CS- estimates are drawn from two distributions with different means, rather than the same mean. In other words, we are using a regression model that seeks to predict the known psychological state (dependent variable) from the estimated psychological state (independent variable). Note that this is different from a more conventional regression or ANOVA model in which the data are the dependent variable and experimental conditions are the independent variable. This difference is important. In our approach, when comparing different methods, the dependent variable (the true state) will be the same, and the independent variable (the state estimates) will differ. This means that the total sum of squares (TSS) in the model will be constant. Thus, we can use the residual sum of squares (RSS) to compute model evidence and compare models - i.e. compare evidence for the statement that the method's estimates of the psychological state predict the true psychological state. We have termed this "predictive validity". Note that the model is not predictive

in time - we are not trying to predict unknown data values - we are trying to predict true psychological state from the estimated state.

To quantify model evidence, PsPM uses the following approximation to Akaike Information Criterion (AIC) [2]:

$$AIC = n \log(RSS/n) + 2k = -2 \log(L) + 2k,$$

where n is the number of data points in the predictive model, L is the maximum of the likelihood function, and k the number of parameters in the predictive model. k is constant for all methods that are evaluated in a methods comparison. We only interpret AIC differences, so this complexity term disappears from methods comparison. AIC differences are termed log Bayes Factors (LBF) and in our case quantify the relative evidence that one method's estimates predict the true psychological state, relative to the other method. An absolute AIC difference of greater than 3 is usually regarded as significant. This is because for a classical significance threshold of $\alpha = .05$, the probability of the data given the null hypothesis is $p < .05$. Similarly, for an LBF difference larger than 3, the relative probability that the inferior method predicts the true psychological state given the data is $p < \exp(-3) \approx 0.05$ [3].

All methods included in PsPM have empirically been shown to provide better or equal predictive validity than the best available corresponding conventional index. Although in most validation edexperiments only two conditions need to be distinguished (a discrimination problem), the goal of PsPM is to provide minimum-variance estimates of cognitive processes also in situations in which the cognitive process varies across more than just two levels. This is why we do not use discrimination methods to evaluate the models. Also, since most psychophysiological measures are influenced by a variety of cognitive processes, a inference on a specific process unavoidably rests on a suitable experimental design in which different conditions only differ on this dimension, and not on other dimensions.

Of course, this approach to method comparison can also be used to improve operational indices, or event to create new indices in a blind classification approach based on large data sets.

Historical remark: Some papers from the PsPM team have used the formula: $NLL = n \log(RSS/n)$. If NLL is read as an arbitrary variable name, this formula is consistent with the previous paragraphs, and the resulting NLL differences can be read as Bayes Factors. The significance threshold used in these papers was 3, and hence all conclusions in these papers are also correct. However, note that NLL in this formula is not the negative log likelihood (as confusingly implied in the papers), but really the AIC without complexity correction. The numerical value of the negative log likelihood would in this terminology be $NLL/2$.

3 General model structure

3.1 General

All model in PsPM split the relation between mind and body into two models, a peripheral and a neural model. The peripheral model describes how a neural impulse is converted to a measurable signal. The neural model describes the relation between the psychological process and the neural input into the peripheral system. This distinction is historically based on SCR models. The neural signal that elicits SCR can be measured by intraneural recordings, and its properties are in principle known. Hence it appeared plausible for various research groups to create a peripheral model [4, 5, 6] that takes an arbitrary neural input, and several neural models were then combined with this peripheral model. This distinction has later been used for other modalities, too: first because it appeared simple from a practical standpoint, secondly because it is often plausible to assume that the peripheral process is not directly influenced by psychological states, but only via a neural input. Note, however, that the peripheral/neural distinction in the model implementation is not always consistent with biophysical reality and tends to follow a need for manageable inversion algorithms. Indeed, some models collapse peripheral and stereotypical neural processes into the peripheral model. Examples are the GLMs for fear-conditioned HPR, PSR, and RAR - this is unlike the non-linear SCR model in which parameters of the neural model are estimated explicitly.

3.2 Peripheral models

The peripheral models in PsPM collapse all physiological and biophysical processes involved in the generation of the measured signal. For most psychophysiological measures, these processes are not known at the level of detail required to build true biophysical models from theory. In fact, biophysically inspired models for the best-investigated modality, SCR, tend to not fit all features of the observed data [7, 4]. This is why PsPM uses purely phenomenological models which regard the peripheral system as a black box. By applying controlled inputs into the system, and measuring the output, one can then approximate the workings of this black box in mathematical form, without knowing its content.

Crucially, all models in PsPM assume that the peripheral system can be described by one (or several) linear time invariant (LTI) systems with the defining properties linearity and time invariance. A LTI system is unambiguously described by its response function (RF). By linearity, input and output are linearly mapped so the responses to several inputs can be simply obtained by summing the responses to individual inputs. Time invariance means that the output does not explicitly depend on the time, i.e. that the shape of the RF is constant over time while the amplitude can vary. It is usually also assumed that the RF is constant over individuals, although this assumption is not necessary in the PsPM framework.

In principle, linearity ensures pure summation of two overlapping inputs.

This is not realistic if the system has limited dynamic range and saturates due to a quick succession of inputs (e. g. the heart rate cannot increase indefinitely). One can formulate limits, for each data modality, within which the model is a useful approximation to reality.

For some modalities, the two properties linearity and time invariance can be explicitly tested by direct neural recordings (e.g. for SCR). For other modalities, this is not possible.

Mathematically, the output $y(t)$ of a LTI system can be fully described by convolving input $u(t)$ with the system's response function $h(t)$ and can be written as

$$y(t) = u(t) * h(t) = \int_0^\infty u(t - \tau)h(\tau)d\tau.$$

Note: Convolution is more generally defined by integration over \mathbb{R} . Integrating over \mathbb{R}^+ (or alternatively, setting $h(t) = 0, t < 0$) ensures the causal structure of the model - only past inputs can have an effect only into the future, not future inputs into the past. It also reflects the implementation via Matlab's vector convolution function, `conv.m`

In many cases, the peripheral system is not exactly LTI but can be approximated by the combination of several LTI systems. The common case is the inclusion of RF derivatives to account for between-subject variability in RF shape and latency, and a special case the combination of a dilation and a constriction RF in pupil size modelling. In our terminology, the RF then has k "components": $h(t) = h_{1..k}(t)$.

In such cases, the amplitude estimates for several response functions need to be combined. In PsPM, this is usually (unless indicated otherwise) done by multiplying each component of the RF with its amplitude estimate, and adding them. The peak of highest absolute amplitude is then identified, and its signed amplitude extracted as estimate of neural input amplitude.

Signal frequencies in the data that are not present in the RF do not contribute to the model inversion and can be filtered out. If the true RF were known, the matched filter theorem provides a way of theoretically deriving a filter that maximises the signal-to-noise ratio for the model inversion. In most cases, the true RF is not precisely known, and also varies between individuals. This is why PsPM seeks to empirically determine the filter characteristics that maximise predictive validity of psychological state estimates.

3.3 Neural models

The neural model in PsPM describes the form of the neural input that the peripheral model can take, and thus, the relation between mind and neural system. In general, model inversion benefits from constraining the neural model, i.e. from reducing the number of parameters that have to be estimated. We have empirically shown for SCR models that in many cases, a strongly constrained neural model will result in higher predictive validity [8, 9, 10].

Most PsPM models assume an instantaneous (delta) neural input into the peripheral system at a known time point t_i :

$$u(t) = \delta(t_i).$$

Only the amplitude of the neural input is then estimated, and is taken as estimate of the psychological state. This renders the model suitable for GLM inversion (see below). Less constrained models require non-linear inversion methods and can also deal with variable onset, dispersion, or shape, of the neural input.

3.4 Model inversion

3.4.1 Hierarchical summary statistic approach

PsPM takes a hierarchical summary statistic approach, like many other frameworks for analysis of psychophysiological data. This means, parameters are estimated for each participant separately, either per experimental condition, or per trial with subsequent averaging within the experimental condition. This yields one value per participant per condition, which is then entered into a group-level model. In line with fMRI terminology, we use the terms “first-level” and “second-level” for the individual and group level.

This summary statistic approach offers two advantages over the alternative, multi-level modelling. First, model inversion is very fast. Secondly, in the time-series data analysed in PsPM, errors are usually not independent. This is usually not a problem for parameter estimation but impacts on the effective degrees of freedom and thus renders statistical tests in these models invalid, and this would apply to multi-level models, too. fMRI softwares solve this problem by estimating an auto-regression model on the first level but this is usually done on data from many data channels/voxels, this is not possible for single-channel data in psychophysiology. This is why PsPM does not offer statistical tests on the first level. For the summary statistic approach in PsPM, the dependencies between data points on the first level are unproblematic.

Multi-level modelling would however offer greater statistical power, and we would endorse attempts to implement this in PsPM.

3.4.2 Probabilistic model inversion

All peripheral and neural models in PsPM are approximations to reality. It is hence assumed that there is measurement error (imprecision of the peripheral model) ε in the data, and that the neural input is not truthfully described by the neural model such that it contains latent error, ω . While this distinction between ε and ω is theoretically interesting and often physiologically plausible, the model inversion methods collapse these two sources of error:

$$\begin{aligned} y(t) &= \varepsilon(t) + [u(t) + \omega(t)] * h(t) \\ &= \varepsilon(t) + \omega(t) * h(t) + u(t) * h(t) \end{aligned}$$

$$= \epsilon(t) + u(t) * h(t).$$

3.4.3 General linear convolution model (GLM)

Under the assumption of delta neural model, we can harness GLM to estimate the neural input amplitude. A GLM can be written as

$$Y = X\beta + \epsilon.$$

Here, Y is the vector of observations (time series data), β is a vector of input amplitude parameters and ϵ is the error. X is design matrix in which each column is obtained by convolving impulse functions at known time points (e.g. event onsets for one condition) with each component of the RF. Each column takes the form:

$$X_{ij}(t) = u_i(t) * h_j(t),$$

where $u_i(t)$ is the neural input with unit amplitude for condition i , and j is the index of the RF component. Finally, X also contains a column for the intercept. It is possible to concatenate data from different experimental sessions, and an intercept is modelled for each session. The maximum-likelihood amplitude estimates are then computed using the Moore-Penrose pseudoinverse X^+ , implemented in the Matlab function `pinv.m`:

$$\hat{\beta} = X^+Y.$$

This allows to deal with situations in which X is not of full rank.

3.4.4 Non-linear model inversion

Models in which timing and/or dispersion of the neural input need to be estimated require non-linear model inversion. PsPM contains several efficient non-linear model inversion methods:

- a Variational Bayes (VB) algorithm [11] for dynamic systems. This can be applied either to an entire data set, or on a trial-by-trial basis, and requires the peripheral system to be written in the form of an ordinary differential equation (ODE).
- a Matching Pursuit algorithm that provides a fast approximation to the VB inversion for some models

4 Skin conductance (SCR) models

4.1 General

SCR arise from opening of sweat glands and are elicited via the sympathetic nervous system with negligible parasympathetic transmission (see [12] for the physiology of SCR). Nerve fibres carrying impulses to the sweat glands are termed

“sudomotor nerve” (SN) fibres and can be measured by intraneural recordings. SN fibres are slow C-fibres. From their end terminal, the neurotransmitter Acetylcholine diffuses through the skin to reach sweat glands, a process on the time scale of up to a second.

The frequency and amplitude of SCR is mainly influenced by psychological arousal. Because not all forms of psychological arousal may influence SCR in the same way, we have in the past termed the relevant psychological state “sympathetic arousal” (SA). Hence, the PsPM model is $SA \mapsto SN \mapsto SCR$.

4.2 Peripheral LTI model

4.2.1 Model evaluation

The peripheral LTI model can be evaluated explicitly (by intraneural recordings or stimulation) and implicitly (by assessing properties of the model $SA \mapsto SN \mapsto SCR$, an approach that collapses LTI violations with imprecision in the neural model).

Time invariance: the system’s response does not explicitly depend on time, or in other words, a given input always produces the same output.

- Direct evidence: The amplitude of individual SN bursts is linearly related to the amplitude of ensuing SCR, with a considerable scatter [13]; to the maximal rate of sweat expulsion; and, somewhat more weakly, to the integrated sweat production during the skin response [14]. After initial dishabituation, constant SN stimulation leads to SCR, with constant amplitude and latency [15]. Repeated SN stimulation yields slightly different SCR shapes [16], although this could be due to variation in elicited neural responses that were not measured downstream. In summary, these findings are consistent with (but do not prove or disprove) the time invariance principle.
- Indirect evidence: We have shown that for short events (< 1 s duration) that are separated by at least 30 s, more than 60% of the variance in (high pass filtered) SCR can be explained under an LTI model, for aversive white noise bursts, aversive electric stimulation, aversive pictures, auditory oddballs, and a visual detection task [17]. Is this residual variance (40%) due to violations of the LTI assumptions? We have shown that in the absence of any event for 60 s, signal variance amounts to more than 60% of total variance during stimulus presentation. That is to say, by introducing events, residual baseline variance is reduced by 20%. This suggests that residual variance is not caused by violations of the time invariance assumption but variation of the neural input (for example, spontaneous fluctuations), and observation error.

Linearity: the system’s response does not depend on previous inputs.

- Direct evidence: Latency of sweat expulsion is slightly shortened when sweat expulsion rate is very high (i. e. for very strong SN bursts) but not when SN firing is frequent [14]. SCR to individual SN stimulations depend linearly on skin conductance level, and are slightly suppressed upon repetition of the stimulation after 1 s [18]. This suggests that the linearity principle does not hold under all conditions.
- Indirect evidence: The linearity principle amounts to saying that SCR are not influenced by the (preceding) baseline signal. We tested this assumption by presenting two subsequent aversive white noise bursts with an inter stimulus interval (ISI) of either 2 s, 5.5 s, or 9 s, such that the baseline signal at these three time points differed markedly. Violations of the linearity principle in the peripheral system would imply that the amplitude of the subsequent response is dependent on the baseline signal, and thereby, upon the ISI. The second response was always smaller than the first. However, this was not dependent on the ISI, and hence not on the baseline signal. We interpret this effect as central repetition suppression (of the neural inputs into the peripheral system) and conclude that linearity is appropriate for the peripheral system. In other words, the peripheral response to one input is not modulated or affected by the response to another, even when they overlap in time [17].

Model limits Both properties appear good approximations to reality as long as the time interval between two SN firing bursts is not very short (< 2 s) or when the SN firing burst is not extremely strong. It would be possible to model non-linearities in a linear model, using Volterra kernels, as in the analysis of functional magnetic resonance images in the software SPM [19, 20]. Such possibility is however not implemented in PsPM.

4.2.2 Skin Conductance Response Function (SCRF)

The peripheral model in its general form does not specify a particular form of the SCRF. There are three principled ways of defining a SCRF in PsPM:

1. Individual response function. The most precise option is to measure the SCRF for each individual by providing brief inputs into the peripheral system and measuring the response. PsPM allows specifying individual response functions. The benefit of this approach has not been empirically tested.
2. Canonical response function. The most parsimonious method is to use a so-called canonical SCRF which is assumed to be constant across individuals. We have previously shown that a canonical SCRF can explain on average 50% of the variance in individual SCR elicited by various stimuli, while individual SCRFs explain about on average 75% of the variance

[17]. Using a canonical SCRF, linear and non-linear models show a good predictive validity, superior to peak-scoring methods [8, 10].

3. Constrained response function. One can estimate an SCRF from the data of an actual experiment and use this for analysis. It is usually necessary to constrain the shape of the SCRF to make the model estimable. PsPM provides two options for this:
 - In GLM, one can estimate parameters of the (orthogonalised) time derivative of the SCRF. In order to combine this with the canonical SCRF, the response can afterwards be reconstructed for each experimental condition, and the peak amplitude taken as estimate of SA. This approach has higher predictive validity than using the canonical SCRF alone, or using a less constrained SCRF (canonical with time and dispersion derivative) [8].
 - In the non-linear model for event-related SCR, one can use the combined data from all evoked responses from one individual to estimate an SCRF. This approach only considers data within the inter-trial interval. In a validation experiments study with ITI of 7-11 s, this had lower predictive validity than using the canonical SCRF, and we would not recommend it unless the ITI is longer than 20 s, so that the SCRF tail can be unambiguously estimated [10].

Canonical Skin Conductance Response Function The canonical SCRF that is currently implemented was derived from a large dataset of 1278 SCRs from 64 individuals subjected to different experimental manipulations (white noise 85 dB and 95 dB, painful electric stimulation, aversive IAPS pictures, detection of auditory oddballs, detection of a visual target in a stimulus stream). We extracted and mean-centred the 30 s following each stimulus onset and performed a principal component analysis. The first principal component served as empirical SCRF [17].

Formulation for linear models The first PCA component of the empirical SCRF was approximated was fitted by a Gaussian smoothed bi-exponential function (also named bi-exponentially modified Gaussian function), and this provided better fit than other function categories, in particular Gaussian smoothed monoexponential function, exponential-Gaussian hybrid function, or smoothed sigmoid-exponential function. The function is thus defined as

$$h(t) \propto \int_0^t N(t-\tau) (E_1(\tau) + E_2(\tau)) d\tau, \quad t \geq 0, \quad (4.1)$$

$$N(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(t-t_0)^2/2\sigma^2},$$

$$E_i(t) = e^{-\lambda_i t},$$

with estimated parameters: $\hat{t}_0 = 3.0745$ seconds for peak latency; $\hat{\sigma} = 0.7013$ for definition of the rise time; $\hat{\lambda}_1 = 0.3176$ and $\hat{\lambda}_2 = 0.0708$ to define the two decay components. This function is normalised to its maximum such that an infinitely short SN impulse with unit amplitude elicits an SCR with unit amplitude. This renders parameter estimates from linear models easily interpretable in relation to conventional (peak-scoring) analysis.

Historical remarks:

- (a) The appendix of [8] contains a typographic error in the definition of the canonical response function, in particular in the integration limits of eq. (4.1). However, in all versions of the software (PsPM 1.0-2.x) the canonical SCRf was constructed using the Matlab function `conv()` which defines vector convolution analogous to the integral defined above. This implementation has not changed since the initial formulation of the model.
- (b) The initial formulation of the SCRf [5] used a Gaussian-smoothed Gamma distribution, based on a smaller dataset. In the extended data set published in [8], the polynomial part of the Gamma distribution was estimated to be one, resulting in a Gaussian smoothed exponential function.

Formulation for non-linear models An alternative formulation is provided for non-linear models which require a definition of the SCRf in the form of an inhomogeneous ordinary differential equation (ODE). We use an third-order linear ODE to describe the data $y(t)$:

$$\ddot{y} + \vartheta_1 \dot{y} + \vartheta_2 \dot{y} + \vartheta_3 y - u(t - \vartheta_4) = 0; \quad (4.2)$$

where dot notation is used for time derivatives, and this formulation embeds convolution of the SCRf with the SN time series. Parameters were estimated from the empirical SCRf by using a Gaussian bump as canonical SN input (see section on SN below) as $\hat{\vartheta}_1 = 1.342052$, $\hat{\vartheta}_2 = 1.411425$, $\hat{\vartheta}_3 = 0.122505$, $\hat{\vartheta}_4 = 1.533879$. Amplitude of the response function is rescaled such that a canonical Gaussian bump SN impulse with unit amplitude elicits an SCR with unit amplitude.

Formulation for spontaneous fluctuations For modelling spontaneous fluctuations (SF), a different database was used that contained 1153 semi-automatically detected SF from 40 male participants [21]. The first PCA component was taken as empirical SCRf which has slightly different shape than the empirical SCRf for evoked responses. A number of reasons may account for this difference, from participant selection over data pre-conditioning to differences in the canonical SN input. In the absence of further knowledge about the reason for this difference, we propose to use this empirical response function for SF. We estimated the ODE parameters (eq. 4.2): $\hat{\vartheta}_1 = 2.1594$, $\hat{\vartheta}_2 = 3.9210$, $\hat{\vartheta}_3 = 0.9235$, $\hat{\vartheta}_4 = 1.533879$ seconds. Amplitude of the response function is rescaled such that a canonical Gaussian bump SN impulse with unit amplitude elicits an SF with unit amplitude.

Note: In the Matlab implementation, the third order ODE is converted to a 3-dimensional system of first-order ODEs. In that process, the order of the parameters $\vartheta_{1..3}$ is reversed, and they are renamed. With substitutions $y_1 = y$, $y_2 = \dot{y}$, $y_3 = \ddot{y}$, the ODE becomes:

$$\begin{aligned} \dot{y}_1 &= y_2 \\ \dot{y}_2 &= y_3 \\ \dot{y}_3 &= -\vartheta_1 y_3 - \vartheta_2 y_2 - \vartheta_3 y_1 + u(t - \vartheta_4) \end{aligned} \quad .$$

4.3 Neural model and model inversion

4.3.1 General Linear Model (GLM) for evoked SA

This model was developed for experiments in which short experimental events with evoke SA with amplitude a . For each experimental condition i with onset vector t_{o_i} , we assume $u_i(t) = a_i \delta(t_{o_i})$. See 3.4.3 for details on the model inversion.

4.3.2 Non-linear model (DCM) for event-related SA

This model [22] assumes that event-related SA with amplitude a causes a Gaussian bump-like SN firing burst after some delay and with a specified dispersion. For each experimental event:

$$u_{exp}(t) = a \exp \frac{-(t - \mu)^2}{2\sigma^2} + \omega, \quad 0 < \mu < \mu_{max}, \quad \sigma_{min} < \sigma < \sigma_{max}.$$

For situations in which short external stimuli elicit SA, this model uses a canonical central burst latency of zero and dispersion of $\sigma_e = 0.3$ seconds (“fixed response”). For situations in which central processes translate SA into SN with unknown parameters, latency and dispersion are estimated from the data, alongside the SA amplitude, using the following constraints: $\sigma_{min} = 0.1$, $\sigma_{max} = 0.5\mu_{max}$ where μ_{max} is the maximally allowed response latency (“flexible response”).

The full model also accounts for spontaneous fluctuations (next subsection) and baseline changes between trials and can be written as:

$$y(t) = y_{exp}(t) + y_{SF}(t) + y_{SCL}(t) + \epsilon$$

The SCR components are defined by eq. (4.2) with respective parameters and a respective input function $u(t)$. Specifically, the experimental SCR component models evoked and event-related responses, and the SF component models spontaneous fluctuations between trials (part of the latent error). The SCL term is an explicitly modelled error term that absorbs baseline fluctuations and is defined as

$$u_{SCL}(t) = a \exp \frac{-(t - \mu)^2}{2\sigma^2}, \sigma = \sigma_0$$

where dispersion is set to $\sigma_0 = 1.0$ seconds, and μ is estimated from the data. By default, PsPM automatically models SN bursts that occur more than 5 s after the previous trial, and more than 2 s before the next trial. These limits ensure that the modelled SCL and SF do not absorb variance caused by the experiment. The use of different limits has not empirically been tested.

In this model, the parameter space is too large to invert it at once. Inversion is done in a trial-by-trial approach: a number of trials, $T_{1..n}$ is inverted. The ensuing parameter estimates for T_1 are extracted, and the parameter estimates for $T_{2..n}$ are used as prior values for the next inversion for trials $T_{2..n+1}$ where the estimated hidden state values at the start of trial 2 are taken as starting values of the hidden states x . This is continued until all trials have been estimated. This scheme ensures that inversion is kept tractable, and at the same time overlapping responses are taken into account. It also means that estimation errors accumulate over trials which is why part of the latent error is explicitly modelled as SF and SCL. At an inter trial interval of around 10 seconds, inverting 2 or 3 trials at the same time yields comparable predictive validity [10].

4.3.3 Non-linear model for tonic SA (spontaneous fluctuations, SF)

Spontaneous SN bursts cause spontaneous fluctuations (SF) in skin conductance. The number of spontaneous SN bursts is thought to depend on SA. Each spontaneous SN burst is modelled as a Gaussian bump with unknown timing and amplitude and fixed dispersion. For each spontaneous SF burst:

$$u_{SF} = a \exp \frac{-(t - \mu)^2}{2\sigma^2} + \omega, \sigma = \sigma_0, a > 0$$

The dispersion is set to $\sigma_0 = 0.3$ seconds. This model is inverted using a Variational Bayes algorithm [23, 11]. Because the number of SN bursts is difficult to estimate directly, the SF model inversion uses a fixed rate of SN bursts (set to $f = 0.5$ Hertz by default) the amplitude of which is estimated from the data. An amplitude threshold is defined to separate “true” SN bursts from noise. An amplitude threshold of 0.1 μ S rendered the predictive highest validity in a validation paper [24]. The results from this paper have been replicated in an unpublished re-analysis using AIC as objective function in a manner similar to [8]. Re-analysing the second data set described in [24], the optimal threshold was between 0.15 - 0.20 μ S. Further systematic research is needed to fine tune the optimal threshold.

Furthermore, PsPM uses a Matching Pursuit (MP) algorithm as fast (< 1 s per minute of data) approximation to the DCM inversion (ca. 1 min. per minute of data). In theory, this method is less precise, but empirically it is comparable to DCM results in three different data sets [25].

4.4 Data conditioning

4.4.1 Filtering

Skin conductance signals return to a baseline after an SCR, but this baseline can change over time within a large dynamic range. Such fluctuations of the skin conductance level need to be filtered out to make the data accessible to an LTI model. A unidirectional 1st order Butterworth high pass filter with cut off frequency 0.05 Hz was optimal for GLM [8]. The design matrix of the GLM is filtered with the same frequency to account for distortions of response shape. For the non-linear model (DCM) for event-related responses, an optimal filter frequency was found at 0.0159 Hz when using a canonical SCRF and inversion of 2 trials at the same time [10]. Filter characteristics of SF models have not been investigated. In order to reduce computation load, data are resampled to 10 Hz sampling rate for all data analyses which requires a low-pass filter cut off frequency of 5 Hz.

Historical remark: The SCRF was developed using a high pass filter with cut off frequency of 0.0159 Hz as commonly employed in conventional analysis (bidirectional for phasic responses, unidirectional for spontaneous fluctuations). However, this turned out to not be the optimal filter for GLM in follow-up analyses of optimal data conditioning. Note that the canonical SCRF was developed from data filtered with the original settings, and this has not changed since.

4.4.2 Normalisation

For within-subjects analysis, we propose data normalisation after filtering to remove SCR scaling differences due to peripheral factors such as skin property. This increases predictive validity (unpublished analyses). For methods that yield trial-by-trial estimates, post-hoc normalisation of amplitude estimates across trials, before averaging within conditions, yields even better predictive validity [10]. For between-subjects analysis, this is not an option as it removes between-subjects variance.

4.5 Implicit estimates of tonic sympathetic arousal

Our model for SF implies that

$$\int_I [y(t) - y_0] dt \propto \sum_{i=1}^n a_i$$

where I is a time interval, and $a_{1..n}$ are the amplitudes of the n sudomotor bursts in this interval and y_0 is the skin conductance level at rest. That is, by simply taking the time integral, or area under the curve (AUC), of the baseline-corrected data, we get a measure of the number x amplitude of spontaneous SN bursts [21]. This measure is implemented in the software as well. However, we

have subsequently shown that the number of spontaneous SN bursts is a better predictor of tonic SA than AUC, and hence we recommend to use the non-linear model for tonic SA.

4.6 Comparison with other model-based methods for SCR

Several further approaches to model-based analysis of SCR have been introduced in the literature [26, 4, 6, 7, 27] - for one of them, the implementation is publicly available in the software package Ledalab. In this method, SN is calculated from SCR using a deterministic inverse filter. Peaks in the SN time series are then identified and used as operational index of SA. In a head-to-head comparison, predictive validity to identify states with known SA was compared for experiments involving short stimuli and evoked SA. PsPM had better predictive validity than Ledalab in 4 out of 5 tested contrasts, and equal validity in the fifth. Ledalab did not consistently perform superior to classical peak scoring analysis [9].

4.7 Recommendations

- Experimental design:
 - $\text{SOA} > 2$ s between events eliciting SCR. SCR amplitudes appear to be linear with an SOA of 3.5 s between subsequent stimuli [17] and non-linear with $\text{SOA} < 1$ s [18].
- Model set up:
 - Use GLM wherever possible. GLM is more sensitive than non-linear models in evoked SCR paradigms [8].
 - Use default filter frequencies (0.05 - 5 Hz unidirectional filter for GLM [8]; 0.0159 - 5 Hz bidirectional filter for non-linear model [10]).
 - GLM: include all experimental events that evoke SCR (including block starts, break messages, etc.).
 - GLM: canonical SCRF with time derivative and reconstruction of amplitudes is more sensitive than just canonical SCRF, or SCRF plus time and dispersion derivative [8]. The benefit of individual SCRFs has not been tested.
 - non-linear model: canonical SCRF is more sensitive than using individual SCRFs based on short (~ 10 s) ITIs [10]. The use of individual SCRFs based on long ITI paradigms has not been tested.
 - non-linear model: for fear conditioning paradigms, the best way of modelling anticipatory SCR is currently under investigation. It is possibly suboptimal to model one anticipatory “flexible” response, in particular at longer CS/US SOAs when this flexible response may absorb SCR elicited by US or US omission.

- GLM and non-linear model: z-normalisation of data is recommended for within-subjects designs, and should not be used for between-subjects designs.
- Model inversion:
 - SF model: the VB inversion is theoretically better suited than the MP inversion when the expected number of SF is $> 10/\text{minute}$.
- Post-processing
 - non-linear model: trial-by-trial normalisation of amplitude estimates before averaging within conditions can increase sensitivity in within-subjects designs [10] but should not be used in between-subjects designs.

5 Heart Period (HP) Models

contributed by Philipp C. Paulus and Giuseppe Castegnetti, and edited by Dominik R. Bach

5.1 General

Cardiac rhythm is generated locally in the sinoatrial node, but is modulated by central neural input. Therefore, heart rhythm can be used to infer psychological states. To quantify phasic changes in cardiac chronotropy, two measures are common: heart rate (beats per minute) or heart period (milliseconds). Heart period appears to relate to autonomic input linearly, as revealed in experiments in which autonomic nerves in rodents were electrically stimulated with varying frequencies to elicit heart period changes [28]. This is why PsPM models heart period. Heart period information is only available at discrete time points. To facilitate analysis within the existing algorithms, PsPM assigns each heart period to its following heartbeat and linearly interpolates this time series at 10 Hz resolution.

For the analysis of event-related, i.e. phasic cardiac responses, PsPM includes two models: A model for event-related HPR [29] and a model for fear-conditioned bradycardia [30]. As in previous models for Skin Conductance Responses (SCR), both models are optimised with regard to *predictive validity*, i.e. the ability to separate experimental conditions (e.g., CS+ vs. CS-).

Operational analysis has shown that event-related HPR pattern strongly depends upon properties of the input - i.e. modality, intensity and presentation duration of the stimulus material. It follows that both models can only be applied in experiments with defined stimulus presentation times (i.e. ≤ 1 s for event-related HPR). Pharmacological studies have suggested a differential time course of sympathetic and parasympathetic nervous input, but it is not yet known how this maps onto the response components modelled here.

5.2 Peripheral and neural model

In the absence of information on the timecourse of cardiac information, it is difficult to separate a neural and a peripheral model. Hence, these two are collapsed for the purpose of quick and simple inversion with GLM (see 3.4.3). This means that the two implemented models - for evoked HRP and fear-conditioned HRP - use a different RF, although of course the peripheral system is the same in both cases. Castegnetti et al. [30] have attempted to relate the two models to each other, and to derive the neural model behind fear-conditioned bradycardia (see figure 1 of [30]).

5.3 Model for event-related HPR

The model for event-related HPR [29] was developed on data from 84 participants that underwent three different experiments: An experiment using loud white noise sounds ($\sim 85dB$), an experiment using an auditory oddball task, and an experiment using emotional pictures from the International Affective Picture System (IAPS; [31]). All stimuli were presented with long ITIs (> 30 s) to allow the cardiac system to return to baseline after stimulus presentation and avoid overlapping responses. The first three principal response components were extracted, and individual peaks fitted with Gaussian Functions as RF:

$$h(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(t-\mu)^2}{2\sigma^2}} \quad (5.1)$$

To test whether a modeled peak qualified as a RF, we subjected it to a testing procedure in which we started with a single RF and included further RFs. Specifically, we created a first-level GLM for each participant by convolving the event onsets with the specific subset of RFs, and extracted estimates of the response amplitudes for each RF and condition from the continuous heart period data. In order to qualify as RF, parameter estimates for this RF were either required to depict a stable response (i.e., acceleration or deceleration) across all experiments, tested by a one-sample t-test, or to add to the *predictive validity* of the model. This second criterion was evaluated by subjecting the parameter estimates to a between-subject analysis of variance (ANOVA) testing for a main effect of experimental condition.

Hence, the following steps were taken:

Step 1. Test all potential RFs modeled from PCs individually and retain each single RF if it depicts a stable acceleration or deceleration across all experiments or if it allows separation of at least two of the three experiments. All potential RFs fulfilled one of these criteria.

Step 2. Take the chronologically first RF from Step 1 and combine it with the chronologically second RF from Step 1, or with any other RF that overlaps with this second RF. Orthogonalize each set in temporal order, using a Gram-Schmidt algorithm. Retain the best set if additional RFs allow the separation of the three experiments.

Step 3-5. Take the current set, and add the chronologically next untested

Table 1: Model constants for evoked HPR

Response Function (RF)	Parameters of Gaussian Function	
	μ	σ
1	1.0	1.9
2	5.2	1.9
3	7.2	1.5
4	7.2	4.0
5	12.6	2.0
6	18.85	1.8

Note. μ = mean; σ = standard deviation

RF from Step 1, or any other RF that overlaps in time with this second RF. Repeat the strategy of Step 2, and retain the best set if additional RFs allow the separation of the three experiments.

This testing procedure yielded a basis set of six RFs. Model constants are depicted in Table 1.

In an independent model-validation experiment with short ISI (10 s) that used white-noise sounds of varying intensities (~ 85 vs. ~ 65 dB) and both negative and positive pictures from the International Affective Picture System (IAPS; [31]), the following RFs allowed separation of the different experimental conditions:

RF1 allowed the discrimination of 85 dB white-noise sounds and IAPS pictures as well as Positive and Negative IAPS pictures. RF2 allowed the discrimination of 85 dB and 65 dB white-noise sounds, as well as Positive and Negative IAPS pictures. RF3 allowed the discrimination of Negative and Positive IAPS pictures. RF4 did not allow discrimination of any experimental conditions in the validation experiment, but showed a trend to significance for the discrimination of 85 dB white-noise sounds and IAPS pictures ($p = .051$) and a trend for discrimination of Positive and Negative IAPS pictures ($p = .068$).

According to the listed parameters some of these RFs overlap time point 0 and therefore start before the actual stimulus. In PsPM these negative overlaps are automatically marked as missing epochs and will be removed from data and design matrix before the model inversion takes place.

5.4 Model for fear-conditioned HPR

For the analysis of fear conditioned HPR, we sought to build a data-driven RF for discriminating between HPR to CS+ and CS- [30]. This model-based analysis was developed on the basis of four independent data sets, acquired during diverse implementations of a fear conditioning protocol. The shape of the response was determined by visually identifying, among different function classes, the function that qualitatively best resembled the difference between

grand means. This suggested a gamma distribution to be a good candidate. Hence, we fitted it by finding the values of the shape parameter k , the scale parameter Θ , the time onset x_0 and the amplitude A that minimised the residual sum of squares (RSS) from the gamma distribution

$$y = \frac{A}{\Theta^k \Gamma(k)} (x - x_0)^{k-1} e^{-\frac{x-x_0}{\Theta}}$$

The resulting parameters were $k = 1373$, $\Theta = 0.0311$, $x_0 = -38$, with A left free to vary during the model inversion. We term this the canonical heart period response function (HPRF). By comparing different extensions of this model, we found that the combination of HPRF and its derivative performs the best. The ensuing model-based analysis reliably distinguishes HPR to CS+ and CS-, and does so significantly better than model-free analogues (e.g., peak scoring, area under the curve).

5.4.1 Adaptation to different SOAs

By considering fear conditioning sessions with different SOAs, we investigated which adaptation the RF most likely undergoes when SOA is changed. To do this, we compared different SOA-dependent variations of the winning model, and selected the one with highest predictive validity. Our analysis suggested that the RF is time-locked to the US, with no changes in shape. In the toolbox, the default SOA is set to 3.5 s, but it can be modified to assume any positive value. However, we recommend not using SOAs shorter than 2 s. This procedure has been successfully tested with SOAs of 4 [30] and 6 s [32].

5.5 Data Conditioning

5.5.1 QRS detection

PsPM uses a modified offline version of the Pan & Tompkins [33] QRS detection algorithm (`scr_ecg2hb`). The algorithm analyses slope, amplitude, and width of QRS complexes. It uses digital band-pass filters to reduce noise and its thresholds are periodically adjusted to low values. The algorithm works best on data with a time-resolution of 200 Hz. Data with higher sampling rate will automatically be downsampled to the optimal time-resolution. The QRS complex is marked at the rising edge of the integrated waveform signal that usually corresponds well with the position of the R-spike of the ECG.

For the offline version of the Pan & Tompkins QRS detection algorithm some adjustments were made:

- The originally used cascaded integer filters were replaced by a second order Butterworth filter that approximates the desired passband from 5 to 15 Hz better than the original filters.
- To increase detection accuracy heart rate values were restricted to the interval of 20 bpm (IBI of 3000 ms) to 300 bpm (IBI of 300 ms).

- To allow for a manual inspection and possible correction of detection failures `scr_ecg2hb` also contains a tool to visually inspect the results of QRS detection (see 11.2). In order to manually check only those QRS complexes that are likely to be wrong, only those IBIs are checked that fall outside a user-defined range. To avoid the introduction of bias, the rater should blind to the experimental conditions during manual correction of the QRS detection.

Depending on the quality of the recordings `scr_ecg2hb` can achieve a very high accuracy in detecting QRS complexes of up to 99.66% [29].

5.5.2 Interpolation and Filtering

To transform the discontinuous heart-beat information into a continuous signal of heart-period, the heart-beat events are interpolated at a fixed sampling rate of 10 Hz using the built-in function `scr_hb2hp`. The interpolation shifts some early evoked responses such that they appear to start before an event - this is automatically being taken care of by a response function that starts slightly before an event definition.

Before obtaining parameter estimates for the individual response functions the interpolated heart beat time-series is filtered with a second-order Butterworth band-pass filter. For evoked HPR, PsPM uses a pass band of 0.01-2 Hz [29]. For fear-conditioned HPR, PsPM uses a 0.015-0.5 Hz bidirectional 6th order Butterworth filter (cf. [30]).

5.6 Recommendations

- Experimental design:
 - evoked HPR model: use only those RFs that peak within the SOA between subsequent events that elicit an HPR. A formal test of the linearity assumption has not been done yet. Therefore, the number of RFs that can be applied depends upon the SOA.
 - fear-conditioned HPR: use default model for CS/US-SOAs between approximately 2-8 s. The model is tested for 3.5 - 6 s.
- Model set up:
 - Use default filter frequencies (0.01 - 2 Hz unidirectional 2nd order Butterworth filter for evoked HPR [29]; 0.015 - 0.5 Hz bidirectional 6th order Butterworth filter for fear-conditioned HPR [30], although there is apparently no strong impact of filter frequency.

6 Pupil size response (PSR) models

contributed by Christoph W. Korn

6.1 General

Pupil size is under control of two antagonistic muscles [34]: Dilation (mydriasis) results from sympathetic inputs on the M. dilatator pupillae. Constriction (miosis) results from parasympathetic inputs on the M. sphincter pupillae. Pupil size reacts to changes in (il)luminance but also to many cognitive processes including attention, perception, memory, and emotion (see [35] for references). Such cognitive processes are supposed to be relayed via the Edinger-Westphal nucleus and noradrenergic inputs into the locus coeruleus, among others [34]. On the basis of two experiments that elicited (il)luminance changes, we have developed a model for steady state pupil size and, more importantly, an model for changes of pupil size that is based on two LTI systems. These LTI systems can be harnessed to infer the neural input into the pupillary system that is elicited by cognitive processes (under the assumption of a common final pathway of (il)luminance-mediated inputs and cognitive inputs). We have also developed and validated a specific LTI system that allows distinguishing responses to CS+US- and CS- in fear-conditioning setups employing different sensory modalities and timings (Korn et al. under review). In this latter model, neural and peripheral system are collapsed for the purpose of quick and simple inversion with GLM (see 3.4.3).

6.2 Model for pupil size changes elicited by (il)luminance changes

The system controlling pupil size is non-linear. To be able and use linear methods for analysis, PsPM splits the model into several parts.

6.2.1 Model for steady-state pupil size

An exponential function is used to relate illuminance (in $[lx]$) or luminance (in $\frac{cd}{m^2}$) to steady-state pupil size (in arbitrary units as determined by the Eyelink system or in mm). These functions were specified on the basis of the first experiment described in [35] (see 11.4). The functional relationship should cover the (il)luminance range employed in most cognitive experiments. An extension that is similar within the specified (il)luminance range but extends across a wider range can be found in [36]. Whether this non-linearity occurs in the peripheral or neural system is currently not known.

$$d(E_v) = C + A \exp(BE_v)$$

Here, d is the z-scored steady-state pupil diameter and E_v is the respective illuminance level in (in $[lx]$). We obtained the following parameter values: $A = 49.79$; $B = -0.50[\frac{1}{lx}]$; $C = -1.05$.

6.2.2 Model for pupil dilation/constriction

Dilations and constrictions differ in shape, and can thus not be modeled by a single LTI system (which would assume that positive and negative changes do

not differ in shape but just in sign). Hence, we identified a combination of two LTI systems that provide a good approximation of pupil size changes elicited by (il)luminance changes (see first two experiments in [35]). The first LTI-system describes changes to continuous (il)luminance inputs and the second LTI-system models the difference between constriction and dilation. The second system thus receives a brief input for any increase in (il)luminance. Both systems are specified by canonical response functions that take the form of gamma probability density functions.

$$d(t) = c \frac{(t - t_0)^{k-1} \exp(-(t + t_0)/\theta)}{\theta^k \Gamma(k)}$$

where d is the z-scored steady-state pupil diameter, t is time, Γ is the gamma function, and k , θ , and t_0 are free parameters. The fitted parameter values were: System 1: $k = 2.40$, $\theta = 0.29s^{-1}$, $c = 0.77$; System 2: $k = 3.24$, $\theta = 0.18s^{-1}$, $c = 0.43$. Since the latency of the empirical responses was around 200 ms, t_0 was set to 200 ms prior to fitting. (We also modelled the first system with a Gaussian smoothed biexponential function; $d(t) = aN(t) * (E_1(t) + E_2(t))$; where $*$ is the convolution operator; $N(t)$ is a centered Gaussian function $N(t) = (2\pi\sigma^2)^{-0.5} \exp(-t^2/2\sigma^2)$ and $E_1(t)$ and $E_2(t)$ are exponential functions of the form $E(t) = \exp(-\lambda t)$; parameter values: $\sigma = 0.27$, $\lambda_1 = 2.04s^{-1}$, $\lambda_2 = 1.48s^{-1}$, $a = 0.004$).

In GLM-based analyses, these systems explain considerable variance in pupil size time series in two experiments with (il)luminance inputs of long and short duration (with the second LTI system being particularly relevant for brief, i.e., sub-second, inputs). The modeled pupil size time series can be easily specified given a time series of (il)luminance values (see 11.4). These time series can be used as nuisance regressors in GLMs. The specified canonical response functions can also be used to estimate the shape (i.e., the temporal characteristics) of likely inputs into the pupillary systems. We provide examples for this for auditory oddball tasks with three different timings, for an emotional words task, and for a visual detection task (see [35]).

6.3 Model for pupil size changes elicited by fear conditioning

This model collapses peripheral and neural processes into one RF, in order to use GLM for the inversion. On the basis of four experiments employing simple and complex auditory, visual, and somatosensory CS, we have determined a canonical response function that reliably distinguishes pupil responses to CS+US- and CS- (Korn et al. under review). Predictive validity exceeds (or is at least equal to) peak scoring and calculating the area-under-the-curve. The response function was initially based on a CS to US SOA of 3.5 s but the same function can be used for an SOA of 6 s. The overall best performing model did not include the temporal derivative but this is still accessible in PsPM. See: 12.5. The gamma probability density function followed the same form specified above

with the parameter values $k = 6.03$, $\theta = 0.73s^{-1}$, $c = 1.6$, $t_0 = 0.029$ (t_0 was fitted for this model).

6.4 Data preconditioning

We provide procedures to import pupil data from Eyelink files (`scr_get_eyelink`). Missing data due to blinks or slight head movements can be linearly interpolated before z-scoring. These missing data can then be retained, or not, for the GLM. Additionally, pupil size may be artificially influenced by foreshortening, if the participant does not maintain fixation. To account for this, we have included a function that determines these instances (see 11.5). For this, the user has to specify the distance between screen and eye, the screen size, the position of the fixation point (by default the middle of the screen is assumed but additionally a time series of fixation points can be specified), and the threshold for exclusion set in degrees of visual angle. For our analyses, we found that filtering provided equal or worse proportions of explained variance and therefore we do not usually use filtering although this may be beneficial for other experimental designs.

7 Respiratory response models

contributed by Giuseppe Castegnetti and Dominik R Bach

7.1 General

Brain stem centres regulate respiration via autonomic nervous efferents, and these centres are influenced by higher cognitive processes [37, 38]. This may allow inferring psychological states from measured respiration, although it is not very well known which psychological variables or events elicit phasic respiratory responses. PsPM implements four models for respiratory responses, derived from a single chest belt system. In principle, this only allows assessing respiration period, while for precise quantification of respiratory amplitude, a double-belt system would be required to measure both thoracic and abdominal compartments [39]. However, if the ratio between thoracic and abdominal contribution is relatively constant within any individual, it may still be possible to approximate respiratory amplitude up to a linear constant from the single-belt system. We confirmed in [40] that respiration amplitude from a single chest belt system can be usefully analysed. PsPM considers the following measures:

- Respiration period (RP) is the duration of a breathing cycle. PsPM models RP rather than the more common respiration rate, its inverse, in analogy to analysis of event-related cardiac responses where heart period has been shown to linearly relate to autonomic nervous system input [28]
- Respiration amplitude (RA) is the amplitude in rib cage excursion on that cycle, which linearly relates to current tidal volume (VT) [39].

- Respiration flowrate (RFR), RA/RP, which is linearly related to tidal volumetric flow rate, i.e. tidal volume per time unit. RFR is computed per cycle with variable duration. Otherwise it is similar to minute volume, or RLL (respiration line length), which are computed over fixed intervals.

In these measures, we identified the following pattern of phasic responses [40]:

- Respiratory period responses (RPR) are elicited by various external events (aversive sounds, electric shocks, picture viewing, visual detection) and reliably distinguish events from non-events
- Respiratory amplitude responses (RAR) are elicited by aversive sounds and shocks, and by picture viewing, and less so by picture viewing (including aversive pictures). RAR are also elicited by fear-conditioned stimuli.
- Respiratory flow-rate responses (RFRR) are elicited by aversive sounds and shocks, and by picture viewing, and less so by picture viewing (including aversive pictures).

7.2 Peripheral and neural model

In the absence of information on the timecourse of cardiac information, it is difficult to separate a neural and a peripheral model. Hence, these two are collapsed for the purpose of quick and simple inversion with GLM (see 3.4.3). This means that the two implemented models for RAR - evoked RAR and fear-conditioned RAR - use a different RF, although of course the peripheral system is the same in both cases.

7.3 Models for evoked respiratory responses

These models are based on responses from 46 participants and on the following task conditions: visual detection, aversive electric shocks, IAPS picture viewing. The model was validated on an independent sample of 20 participants and the following task conditions: aversive and less aversive white noise sounds, positive and negative IAPS picture viewing.

We modelled responses with Gaussian functions:

$$h(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\mu)^2}{2\sigma^2}}.$$

Model constants after filter optimisation are summarised in table 2. Later response components that were visually identified in the development data set did not contribute to detecting overall responses or separating experimental conditions. Modelling the time derivative of the RF improved the RA and RFR models, but not the RP model [40].

Table 2: Model constants for evoked respiratory responses

Response Function (RF)	Parameters of Gaussian Function	
	μ	σ
RPR	4.20	1.65
RAR	8.07	3.74
RFRR	6.00	3.23

Note. μ = mean; σ = standard deviation

7.4 Model for fear-conditioned RAR

After showing that RAR may be better suited to distinguish cognitive processes than respiration period [40], we investigated whether RAR allow assessment of fear memory in cued fear conditioning. Following the same procedure as in [30], we built the RF from data collected during six experiments, involving diverse stimuli and two types of breathing belts (bellows and cushion systems). The ensuing winning model was the combination of an early and a late response components, modelled by gamma distributions

$$y = \frac{A}{\Theta^k \Gamma(k)} (x - x_0)^{k-1} e^{-\frac{x-x_0}{\Theta}}$$

with parameters $k_e = 2.570 * 10^7$, $\Theta_e = 3.124 * 10^{-4}$, $x_{o,e} = 8.024 * 10^3$ and $k_l = 3.413$, $\Theta_l = 1.107$, $x_{o,l} = 7.583$, respectively. This method distinguishes RAR to CS+ and CS- better than model-free scoring of RAR (e.g., peak scoring). Compared to other measures of fear learning, RAR turn out to perform similar to SCR, but are less sensitive than HPR. By analysing data from experiments involving SOAs of 3.5, 4, and 6 s, we inferred that the RAR are most likely time locked to the US, meaning that both components of the RF must be shifted in time as a function of the SOA. To avoid deformation of the early RF due to violations of the linearity assumptions, however, we recommend to use this method only with experiments involving SOAs longer than 2.5 s.

7.5 Data Conditioning

7.5.1 Breathing cycle detection

Bellows system Transducer output is filtered offline with an anti-aliasing bidirectional first-order Butterworth low-pass filter and a cut-off frequency of 5 Hz. Data are then downsampled to 10 Hz resolution. Respiration traces are mean-centred, filtered with a bidirectional Butterworth band pass filter and cut-off frequencies of 0.01 Hz and 0.6 Hz, and median filtered over 1 s. A negative zero-crossing is taken as start of inspiration. After each detected cycle, PsPM imposes a 1 s refractory period, to account for residual signal noise with might cause several zero-crossings on the same cycle. In the validation data set, we compared this method to visual detection as gold standard and found, for the

automated method, a sensitivity of 99.3%, and a positive predictive value of 99.5%. For the time difference between visual and automated detection, we found a median delay of 0.1 s and a standard deviation of 0.1 s [40].

Cushion system For data obtained from the cushion/belt system, the above algorithm must be adapted to account for the different response of cushion/belt system to ventilator activity. Specifically, we defined the onsets of the inspirations as the minima of the respiratory trace. Hence, the algorithm was adapted to extract zero crossings of the derivative of the time series (i.e., the extrema), from which the positive ones (i.e., the minima) were set as the start of the inspiration.

7.5.2 Interpolation and Filtering

To transform the discontinuous RP, RA and RFR information into a continuous signal, they are assigned to the start of the following inspiration cycle and linearly interpolated with 10 Hz sampling frequency. It is also possible to write out the respiration time stamps for quality control. The interpolation shifts some early evoked responses such that they appear to start before an event - this is automatically being taken care of by a response function that starts slightly before an event definition. The best filter frequencies in [40] were: 0.01-1 Hz for RP, 0.001-1 Hz for evoked RA and RFR. For fear-conditioned RA a 0.001-2 Hz bidirectional 6th order Butterworth filter provided the best results (cf. [32]).

7.6 Recommendations

- Experimental design:
 - evoked respiratory response models: make sure the SOA between subsequent events that elicit an respiratory response is longer than the peak of the respective RF. A formal test of the linearity assumption has not been done yet.
 - fear-conditioned RAR: To avoid deformation of the early RF due to violations of the linearity assumptions, however, we recommend to use this method only with experiments involving SOAs longer than 2.5 s.
- Model set up:
 - Use default filter frequencies (0.01-1 Hz for RP, 0.001-1 Hz for evoked RA and RFR. 0.001-2 Hz for fear-conditioned RA.)

Part II

User Guide

8 Installation

You can find and download the PsPM package at the following URL:

<http://pspm.sourceforge.net/>

Decompress and copy the files to any directory of your choice. Then add the PsPM files to the Matlab search path by entering the following command in the Matlab command line:

`addpath([your Matlab path])` where [your Matlab path] is a string of the file location on your hard drive, e.g.

`addpath('C:\Program Files\MATLAB\R2013a\toolbox\PsPM\')`.

Do not add subfolders of the PsPM directory to the matlab path.

Type `pspm` in the command line to start the package. Alternatively, each function can be called individually from the command line. In that case, you can use `scr_init` to load the settings, and `scr_quit` to remove PsPM subfunctions from the path and delete the settings.

The GUI requires Matlab 2007 (R14) or higher for the graphical interface. If you are using command line functions only, it should be possible to use earlier Matlab versions, but this has not been tested. Display of non-linear model inversion may not work properly under Matlab 2014 and upwards due to limitations of an external code.

9 General points

9.1 File types

PsPM knows three different file types:

- Data files - usually the original file name is prepended with 'scr_' during import. Various pre-processing steps prepend additional letters to the name.
- First-level model files - all models use a similar data structure. The name can be freely specified by the user. These files also contain reconstructed responses in GLM, and contrast values.
- Second-level model files. The name can be freely specified by the user.

9.2 Functions that create new data files

- Import - prepended with 'scr_'
- Trim - prepended with 't'

- Artefact removal - prepended with 'm'
- Split sessions - appended with '_sn<nr>'
- Downsample data - prepended with 'd'

These functions ask whether an existing file with the same name should be overwritten - unless you specify 'overwrite' in the options.

9.3 Functions that create or modify data channels in an existing file

- Preprocess heart data
- Preprocess respiration data
- Find valid fixations
- Convert pupil data
- Find startle sound onsets
- Interpolate missing data

These functions allow you to select where to store a modified data channel. The following options exist:

- add: A new channel is created with the new data
- replace: If one or several channels of the output type exists, the last of these will be overwritten. For some functions, this can overwrite the original data, i. e. if a conversion function produces an output of the same type as the input (e.g. convert mm to m). If no channel of the output channel type is found, a channel will be added.

10 Data preparation

10.1 Import

Related function: `scr_import`

Import external data files for use by PsPM. First, specify the data type. Then, other fields will come up as required for this data type. The imported data will be written to a new .mat file, prepended with 'scr_'.

Data Type

CED Spike

Text Text files can only contain numbers (i.e. no header lines with channel names) and one data column per channel. Make sure you use the decimal point (i.e. not decimal comma as used in some non-English speaking countries). At the moment, no import of event markers is possible

Matlab Each input file must contain a variable called data that is either a cell array of column vectors, or a data points \times channels matrix. The import of event markers is supported. Marker channels are assumed to be continuous if the input data is a matrix or if the input data is a cell and the given samplerate is larger than 1 Hz. A sample rate has to be specified for any type of data.

Biopac AcqKnowledge (up to v. 3.9)

exported Biopac AcqKnowledge

bioread-converted Biopac AcqKnowledge (any version) Loads mat files which have been converted using the bioread tool acq2mat. Bioread can be installed using pip (installed by python) or can be downloaded and installed manually from here <https://github.com/njvack/bioread>. It requires python and the python libraries numpy and scipy.

Labchart exported (up to v. 7.1) Export data to matlab format (plugin for the LabChart software, available from www.adinstruments.com)

Labchart exported (v. 7.2 and higher)

VarioPort

Biograph Infiniti exported Export data to text format, both "Export Channel Data" and "Export Interval Data" are supported; a header is required

Mindmedia Biotrace exported

BrainVision

Windaq (Manufacturer's version) Requires an ActiveX Plugin provided by the manufacturer and contained in the subfolder Import/wdq for your convenience. This plugin only runs under 32 bit Matlab on Windows.

Windaq (PsPM Version) Windaq import written by the PsPM team. Is platform independent, thus has no requirements for ActiveX Plugins, Windows or 32bit Matlab. Imports the *.wdq files. Up to now the import has been tested with files of the following type: Unpacked, no Hi-Res data, no Multiplexer files. A warning will be produced if the imported data-type fits one of the yet untested cases. If this is the case try to use the import provided by the manufacturer (see above).

Observer XT compatible

NeuroScan

BioSemi

Eyelink Eyelink output files (with extension *.edf) must first be converted to ASCII format (extension *.asc). This is done with the utility edf2asc.exe (normally included in the Eyelink software in <Path to Program Files>\SR Research\EyeLink\EDF_Access_API\). Otherwise there is a Data viewer, available at <http://www.sr-research.com/dv.html> (registration needed), which installs a utility called 'Visual EDF2ASC'. This also allows the conversion and does not require a license. The composition of channels depends on the acquisition settings. If two eyes were recorded channels will be (Channel id 1-8): Pupil (diameter) L, Pupil R, x L, y L, x R, y R, blink L, blink R. If one eye was recorded, channels will be (Channel id 1-4): Pupil (diameter), x, y, blink.

European Data Format (EDF)

Philips Scanphyslog The physlog ascii file contains 6 channels with physiological measurements:

Channel id	Event type
1	ECG1
2	ECG2
3	ECG3
4	ECG4
5	Pulse oxymeter
6	Respiration

Depending on your scanner settings, there are 10 trigger channels (see complete list below) of which channel 6 marks time t of the last slice recording. After importing, a time window from t minus (*#volumes*) * (*repetition time*) seconds until t should be used for trimming or splitting of sessions to constrain data in the imported file to the EPI recording window and easier matching with experimental events from a separate source.

Available trigger channels are:

Channel id	Event type
1	Trigger ECG
2	Trigger PPU
3	Trigger Respiration
4	Measurement ('slice onset')
5	Start of scan sequence
6	End of scan sequence
7	Trigger external
8	Calibration
9	Manual start
10	Reference ECG Trigger

Data File(s)

Specify which data file(s) to import. You can import multiple files that all have the same structure.

New Channel

Define each channel that you want to import.

Channel Type Specify the type of data in this channel. Currently supported data types: SCR, ECG, heart beat markers, interpolated heart rate, interpolated heart period, respiration traces, interpolated respiration period, pupil size, marker channels.

Channel /Column Number Specify where in the original file to find the data - depending on your data type this will be a channel or column number. You can either specify a number (i. e. the n-th channel in the file), or (for many data types) search for this channel by its name. Note: the channel number refers to the n-th recorded channel, not to its number during acquisition: if you did not save all recorded channels, these might be different for some data types.

- Search [if available]: Search for channel by its name – this only works if the channel names are unambiguous, and not for all data types.
- Specify Channel Number [if required, otherwise a default channel number will be assigned]: Specify the n-th channel. This counts the number of channels actually recorded.

Sample Rate [if required] Sample rate in Hz (i. e. samples per second). For most data types, this is read from the original data file.

Transfer Function [for SCR data only] Enter the conversion from recorded data to Microsiemens.

The transfer function supports two recording systems, which are either a conductance based system (default) or a resistance based system. Depending on the recording system the relation between measured conductance G in μS to recorded voltage U in V is either

$$G = \frac{1}{\frac{c}{U - offset} - R_s}, \quad (10.1)$$

or

$$G = \frac{1}{\frac{U - offset}{c} - R_s}. \quad (10.2)$$

For a transfer constant c in $V/\mu S$ (for 10.1) or in $V/M\Omega$ (for 10.2), series resistor R_s in Ohm, and a fixed offset in V which was added to the initially measured voltage. If there is no offset and series resistor, this is equivalent to

$$G = \frac{U}{c}, U = cG$$

or

$$G = \frac{c}{U}, U = cR = \frac{c}{G},$$

There are three options how to enter this information:

- File: Enter the name of the .mat file that contains the variables: 'c', 'Rs' (in Ohm) and 'offset', 'recsys' (possible values: 'conductance' or 'resistance').
- Input: Enter the transfer constants manually.
- None: No transfer function. Use this only if you are not interested in absolute values, and if the recording settings were the same for all subjects.

10.2 Trim

Related function: `scr_trim`

Trim away unnecessary data, for example before an experiment started, or after it ended. Trim points can be defined in seconds with respect to start of the data file, in seconds with respect to first and last marker (if markers exist), or in seconds with respect to a user-defined marker. The resulting data will be written to a new file, prepended with 't'.

Data file

Choose the data file you want to trim.

Reference

Choose your reference for trimming: file start, first/last marker, or a user-defined marker. All trimming is defined in seconds after this reference – choose negative values if you want to trim before the reference.

File Trim from xx seconds after file start to xx seconds after file start.

- From (seconds after file start): Choose a positive value.
- Trim To (seconds after file start): Choose a positive value larger than the 'from' value.

First/Last Marker Trim from xx seconds after first marker to xx seconds after last marker.

- From: (seconds after first marker): Choose a positive (after first marker) or negative (before first marker) value.
- To: (seconds after last marker): Choose a positive (after last marker) or negative (before last marker) value.
- Marker Channel: If you have more than one marker channel, choose the reference marker channel (default: use the first marker channel in the file)
 - Default (first marker channel=0)
 - Number

Any Marker Trim from xx seconds after any marker of your choice to xx seconds after any marker of your choice.

- From: Choose marker number and trimming point in seconds after this marker.
 - Marker Number x: Choose an integer value.
 - Seconds after Marker x: Choose a positive (after this marker) or negative (before this marker) value.
- To: Choose marker number and trimming point in seconds after this marker.
 - Marker Number y: Choose an integer value.
 - Seconds after Marker y: Choose a positive (after this marker) or negative (before this marker) value.
- Marker Channel: If you have more than one marker channel, choose the reference marker channel (default: use the first marker channel in the file)
 - Default (first marker channel=0)
 - Number

Overwrite Existing File

Choose “yes” if you want to overwrite existing file(s) with the same name. Default: no.

11 Data preprocessing**11.1 Preprocess heart data**

Related function: `scr_ecg2hb`, `scr_hb2hp`, `scr_ppu2hb`

Convert ECG to heart beat detects QRS complexes in ECG data and write timestamps of detected R spikes into a new heart beat channel. This function uses an algorithm adapted from [33] (see 5.5.1). Hidden options for minimum and maximum heart rate become visible when the job is saved as a script and should only be used if the algorithm fails.

Convert Heart Beat to heart period interpolates heart beat time stamps into continuous heart period data and writes to a new channel. This function uses heart period rather than heart rate because heart period varies linearly with ANS input into the heart.

Convert Peripheral pulse oximetry to heart beat first creates a template from non-ambiguous heart beats. The signal is then cross correlated with the template and maxima are identified as heart beats.

Convert ECG to heart period allows to directly convert continuous ECG data into continuous heart period data. This function is a combination of the two functions “Convert ECG to heart beat” and “Convert Heart Beat to heart period”.

If, for ECG conversions, the semi automatic mode is enabled, the ECG editor will be shown. This allows manual inspection and correction of potentially wrong HB events. If the semi automatic mode is disabled, the conversion is done automatically, without showing the ECG editor. See ECG editor (11.2) for further information.

Data File

Specify data file.

Preprocessing

Add different preprocessing steps here. The converted data will be written into a new channel in the same file.

Convert ECG to Heart Beat

Convert ECG data into Heart beat time stamps.

Channel Number of ECG channel (default: first ECG channel).

Options

- Semi automatic mode: Allows manual correction of all potential beat intervals (default: off).

Convert Heart Beat to Heart Period

Convert heart beat time stamps into interpolated heart period time series. You can use the output of the ECG to Heart beat conversion, or directly work on heart beat time stamps, for example obtained by a pulse oxymeter.

Channel Number of Heart Beat channel (default: first Heart Beat channel).

- Default: First Heart Beat channel
- Number
- Processed channel: Convert a channel already preprocessed with ECG to Heart beat. Specify the preprocessed channel with a number corresponding to the position in the list of preprocessings.

Sample rate Sample rate for the interpolated time series (default: 10 Hz).

Limit Define unrealistic values which should be ignored and interpolated.

- Upper limit: Values bigger than this value (in seconds) will be ignored and interpolated. Default: 2
- Lower limit: Values smaller than this value (in seconds) will be ignored and interpolated. Default: 0.2

Convert ECG to Heart Period

Channel Number of ECG channel (default: first ECG channel).

Options

- Semi automatic mode: Allows manual correction of all potential beat intervals (default: off).

Sample rate Sample rate for the interpolated time series (default: 10 Hz).

Limit Define unrealistic values which should be ignored and interpolated.

- Upper limit: Values bigger than this value (in seconds) will be ignored and interpolated. Default: 2
- Lower limit: Values smaller than this value (in seconds) will be ignored and interpolated. Default: 0.2

Convert Peripheral pulse oximetry to Heart Beat

Channel Number of Peripheral pulse oximetry channel (default: first Peripheral pulse oximetry channel)

Replace output channel

Replace existing conversion(s) with new converted data. If no conversion exists, (a) new channel(s) will be created (default: No).

11.2 ECG editor

Related function: `scr_ecg_editor`

The ECG editor is integrated into the QRS detection (formerly `scr_ecg2hb_qc`) and can also be used offline, after QRS detection. It allows to graphically inspect and correct (if necessary) the detected QRS markers. To facilitate QRS inspection in data sets with known artefact epochs, the user can load epoch files which define such artefact periods. This allows the editor to either ignore or even remove QRS markers which fall into artefact periods.

Startup

The ECG editor can be started from the PsPM window, from the Matlabbatch window or from the command line.

From the command line the ECG editor can be started by typing `scr_ecg_editor(argument)` into the Matlab command line. For this the PsPM folder has to be added to the matlab path beforehand. Arguments are either a data struct (generated usually by `scr_ecg2hb`) or a path to a PsPM file.

Data modes

Similar to the data editor the ECG editor supports two types of operation modes, which depend on the startup arguments.

File mode Is entered when the editor is started from the PsPM window, from the Matlabbatch or when a file path or no argument is specified at the command line startup. If the first argument is a file path, a second (ECG channel) and a third argument (Options struct) is possible. The second argument specifies the ECG channel to be plotted. The third argument is expected to be a struct with the following fields:

- `hb` - specifies a HB channel which contains the QRS markers to be inspected
- `factor` - specifies the minimum factor faulty QRS markers should deviate from the standard deviation (default is 2)

- `semi` - specifies whether to navigate between potentially wrong hb events only (semi mode), or between all hb events (manual mode; semi mode is enabled by default).
- `limits` - with fields 'lower' and 'upper' defines hard limits for the faulty detection (default is 120bpm [upper] and 40bpm [lower])

The second and third argument is optional. In file mode the 'Input / Output' panel on the bottom of the left side is visible. It allows to specify and change input files and channels (ECG and HB) and allows to choose whether the edited data should be added as a new HB channel or replace the existing HB channel.

Inline mode The inline mode is usually used together with `scr_ecg2hb`. Therefore a struct which is generated by the latter function is expected. The following fields are needed for the editor:

- `settings`
 - `.outfact` - specifies to which factor faulty QRS markers should deviate from the standard deviation
 - `.sr` - specifies the sample rate of the data
- `data`
 - `.x` - contains the ecg data values
 - `.r` - contains nx4 vector where n corresponds to the ecg data values and columns 1-4 tell whether there is a QRS marker (column 1-4) and whether a QRS marker is faulty (column 2). Columns 3 and 4 are ignored and regenerated during data inspection
- `set`
 - `.R` - contains sample ids of all the QRS markers

Editor output

The output always contains as a first argument a status (sts). If the status equals 1 no error happend while creating the output. Otherwise the editor could not successfully create the output. The second output depends on the Data mode and in file mode contains the channel id of the written channel. In inline mode the second output argument is a data vector which contains the sample ids of the resulting QRS markers.

Data inspection

Navigation The ECG editor uses QRS markers as anchor points for the navigation. One option to navigate between QRS markers is to use the listbox placed in 'Heart beat events' on the right side of the plot. Selecting a QRS

marker in the listbox will cause the plot to center the selected marker with some space left before and after depending on the zoom state. If manual mode is active, the listbox contains all QRS markers available (all colors), otherwise it will only contain QRS markers marked as faulty (orange). The navigation buttons ('<<' and '>>') below the listbox allow moving back and forth in the plot. In manual mode the step size equals the size of the plot window. If manual mode is inactive, the next/previous step equals jumping to the next/previous faulty QRS marker.

Zooming The zoom buttons are placed on the upper right. Zooming in will cause the time window to be shortened by the factor of two. Zooming out will cause the time window to be extended by the factor of two.

Add QRS marker The button for this is placed on the upper right side. Once clicked the cursor will turn into a crosshair. After that, clicking on the plot will cause an additional QRS marker to be added at that position (a green QRS marker appears).

Remove QRS marker The button is also placed on the upper right side. The cursor as well will turn into a crosshair but different to adding QRS markers, clicking on the plot (without releasing the mouse-button) will cause a selection rectangle to be drawn. Upon release of the mouse-button all QRS markers which lie in the selection rectangle will be marked for removal (violet).

Artefact epochs

Settings for the artefact epochs can be found in the 'Artefact epochs' panel.

Load / Disable Clicking the 'Load' button causes a file dialog to appear, which allows to choose a PsPM epoch/timing file containing the definition of artefact epochs. The button 'Disable' will cause the artefact epochs to be unloaded and artefact settings to be disabled. Once an artefact epoch file is loaded, QRS marker stems and listbox font color will turn grey if they lie within an artefact epoch.

Display settings There are three different display options on how to deal with QRS markers which fall into artefact epochs.

- use all QRS markers - do nothing; all markers will be displayed and used for faulty detection
- exclude artefact periods from faulty QRS detection - still all markers will be displayed but QRS marks in artefact periods will be ignored for faulty detection
- hide QRS markers during artefact periods - QRS markers in artefact periods will be hidden and ignored for faulty detection

Output settings There are two different output options on how to deal with QRS marks which fall into artefact epochs.

- include QRS during artefact periods - all markers (faulty and valid) including those lying in artefact periods will be either returned or written to the new HB channel.
- remove QRS during artefact periods - only marks (faulty and valid) outside of artefact periods will be either returned or written to the new HB channel.

Faulty detection

Settings for faulty detection can be changed in the 'Heart beat events' panel. The following settings are possible.

- Detection factor - specifies the minimum factor faulty QRS markers should deviate from the standard deviation
- Upper limit - Heart rates higher than the upper limit will be marked as faulty
- Lower limit - Heart rates lower than the lower limit will be marked as faulty

When changed settings should be applied, clicking 'Find faulty' will cause the plot to be refreshed.

Color coding

Stem / Listbox background colors

- Valid QRS marker \Rightarrow blue
- Faulty QRS marker \Rightarrow orange
- Added QRS marker \Rightarrow green
- Removed QRS marker \Rightarrow violet

Artefact periods The color of QRS markers lying in artefact periods will be converted to greyscale. This applies for the marker stems (not the tips) and the listbox font color.

Matlabbatch

Possible options when the ECG editor is started from Matlabbatch.

Data file Specify the PsPM datafile containing the ECG data

ECG channel Specify the channel containing the ECG data.

- Default
- Number

HB channel Specify the channel containing the HB data.

- None
- Number

Artefact Epochs Specify a PsPM timing file defining artefact epochs.

- Disabled
- File

Faulty detection settings Settings for the faulty detection.

- Factor: The minimum factor potentially wrong QRS complexes should deviate from the standard deviation.
- Limit: Define hard limits for the faulty detection.
 - Upper limit: Values bigger than this value (in bpm) will be marked as faulty. Default: 120.
 - Lower limit: Values smaller than this value (in bpm) will be marked as faulty. Default: 40.

11.3 Preprocess respiration data

Related function: `scr_resp_pp`

Convert continuous respiration traces into interpolated respiration period, amplitude, or RFR, or into time stamps indicating the start of inspiration. This function detects the beginning of inspiration (see 7.5.1), assigns period/amplitude/RFR of the last cycle to this data point, and interpolates data (see 7.5.2). This function outputs respiration period rather than respiration rate in analogy to heart period models - heart period linearly varies with ANS input to the heart. RFR (respiratory flow rate) is the integral of the absolute thorax excursion per respiration cycle, divided by the cycle period. Converted data are written into new channel(s).

Data File

Specify data file. The processed respiration data will be written to a new channel in this file.

Sample Rate

Sample rate for the new channel. Default: 10 Hz. Will be ignored for datatype "respiration time stamps".

Channel

Number of respiration channel (default: first respiration channel).

Options

System type Type of the measuring system: bellows or cushion (default: bellows).

Datatype Choose for each possible process datatype either yes or no (default: yes):

- Respiration period: Create a channel with interpolated respiration period
- Respiration amplitude: Create a channel with interpolated respiration amplitude
- Respiratory flow rate: Create a channel with interpolated respiratory flow rate
- Respiration time: Create a channel with respiration time stamp

Diagnostic plot Specify whether a respiratory cycle detection plot should be created (Yes) or not (No) (default: No).

Replace output channel

Replace existing conversion(s) with new converted data. If no conversion exists, (a) new channel(s) will be created (default: No).

11.4 Prepare illuminance GLM

Related function: `scr_process_illuminance`

Transform an illuminance time series into a convolved pupil response time series to be used as nuisance file in a GLM. This allows you to partial out illuminance contributions to pupil responses evoked by cognitive inputs. Alternatively you can analyse the illuminance responses themselves, by extracting parameter estimates relating to the regressors from the GLM.

The illuminance file should be a .mat file with a vector variable called Lx. In order to fulfill the requirements of a later nuisance file there must be as many values as there are data values in the data file. The data must be given in lux (lm/m²) to account for the non-linear mapping from illuminance to steady-state pupil size. A function to transform luminance (cd/m²) to illuminance values is

provided under PsPM > Data processing > Pupil & Eyetracking. References: [35]

Illuminance file

Select a file that contains illuminance data.

Sample rate

Specify the sample rate of the illuminance data.

Basis function options

Specify options for the basis functions.

- Duration: Specify the duration of the basis function in seconds (default: 20s).
- Offset: Specify an offset of the basis function in seconds (default: 0.2s).
- Dilation: Specify the basis function to model the dilation response.
 - LDRF_GM: Use gamma probability density function to model the dilation response (default).
 - LDRF_GU: Use a smoothed gaussian function to model the dilation response.
- Constriction: Specify the basis function to model the constriction response.
 - LCRF_GM: Use gamma probability density function to model the constriction response (default).

Output directory

Specify the directory where the .mat file with the resulting nuisance data will be written.

Filename for output

Specify the name for the resulting nuisance file.

Overwrite existing file

Choose “yes” if you want to overwrite an existing file with the same name. (Default: No)

11.5 Find valid fixations

Related function: `scr_find_valid_fixations`

Pupil data time series can contain missing values due to blinks and head movements. Additionally, pupil measurements obtained from a video-based eye tracker depend on the gaze angle, therefore breaks of fixation can be excluded. Valid fixations can be determined by setting an a priori threshold with respect to the fixation point (in degree visual angle) for x- or y-gaze-positions. References: [35, 41]

Data file

Specify the PsPM datafile containing the imported eye tracking data.

Eyes

Choose eyes which should be processed. If ‘All eyes’ is selected, all eyes which are present in the data will be processed. Otherwise only the chosen eye will be processed. (All eyes [Default], Left eye, Right eye)

Validate fixations

Disable or enable validation of fixations within a given range on the screen (in degree visual angle).

Disabled Validation of fixation is disabled. Only blinks will result in invalid data points.

Enabled Validation of fixation is enabled. Blinks and invalid fixations will cause invalid data points.

- Visual angle: Range of valid fixations (around a fixation point). The value has to be in degree visual angle.
- Distance: Distance between eyes and screen in mm.
- Screen settings: Attributes of the used screen.
 - Actual hardware aspect ratio: Aspect ratio of the hardware (e.g. [16 9]).
 - Used aspect ratio: Usually, this is the same as the actual aspect ratio. But in some cases, the used aspect ratio may differ (e.g., because the software does not support [16 9] and therefore [5 4] is set).
 - Screen size: Size of the screen in inches (diagonal).
- Fixation point: Point of fixation. Should be given in pixels, according to the x- and y-coordinates set by the eye tracker software.

- Default: If default is set, the middle of the screen will be defined as fixation point.
- File: .mat file containing a variable F with an nx2 matrix. N should have the length of the recorded data and each row should define the fixation point for the respective recorded data row.
- Point: If the fixation point does not change during the acquisition, specify x- and y-coordinates of the constant fixation point.

Channels

Enter a list of channels (numbers or names) to work on. Default is pupil channels. Channels which depend on eyes will automatically be expanded. E.g. pupil becomes pupil_l.

Interpolate

If interpolation is enabled NaN values during blinks and invalid fixations in the selected channels will be linearly interpolated. Otherwise NaN values remain (and the GLM function will treat these data points as missing).

Enabled Interpolation is enabled.

Disabled Interpolation is disabled.

Missing

If enabled an additional channel containing additional information about valid data points will be written. Data points equal to 1 describe epochs which have been discriminated as invalid during validation (=missing). Data points equal to 0 describe epochs of valid data. This function may be enabled in combination with enabled interpolation.

Enabled Missing is enabled.

Disabled Missing is disabled.

Output settings

Define how the validated data should be stored.

File output Write data to a new file or overwrite original data file.

- Overwrite original file: Overwrite original data file.
- Create new file: Write data into given file. The original data will be copied to the given file and the new data channels will, according to the channel output, either be added or replace the original channels.

- File path: Path to new file.
- File name: Name of new file.

Channel output Define whether the data channels should be added or replace the original data channels.

- Add channel: New data channels will be added at the end of the file.
- Replace channel: The function tries to replace the existing data channels. If there is no existing data channel found, the new channel will be added at the end of the file (this very likely applies to the new missing data channels).

11.6 Convert pupil data

Related function: `scr_convert_area2millimeter`, `scr_convert_au2mm`

Data file

Specify the PsPM datafile containing the channels to be converted.

Conversions

Channel Specify the channel which should be converted.

Mode Choose conversion mode.

- Arbitrary units to millimeter
 - Offset
 - Multiplier
- Area to diameter

Channel action

Choose whether to ‘replace’ the given channel or ‘add’ the converted data as a new channel.

11.7 Find startle sound onsets

Related function: `scr_find_sounds`

Translate continuous sound data into an event marker channel. The function adds a new marker channel to the given data file containing the sound data and returns the added channel number. The option threshold, passed in percent to the maximum amplitude of the sound data, allows to specify the minimum amplitude of a sound to be accepted as an event.

Data file

Specify the PsPM datafile containing the imported startle sound data.

Channel

Number of channel containing the startle sounds (default: first sound channel).

Threshold

Percent of the maximum sound amplitude still being accepted as belonging to a sound (important for defining the sound onset). (Default: 0.1 [= 10%]).

Region of interest

Region of interest for discovering sounds. Only sounds between the 2 timestamps will be considered.

- Whole file
- Region

Output

Create channel The new data channel contains by default all marker onsets found in the specified data file. If you want specific sounds defined by a marker, use the diagnostics option.

- Channel action: Add will append the new marker channel as additional channel to the specified PsPM file. Replace will overwrite the last marker channel of the PsPM file (be careful with reference markers). (Default: 'add')

Diagnostic Analyze delays between existing marker channel and detected sound onsets.

- Diagnostics output
 - Text only: Output delay statistics as text (amount, mean, stddev).
 - Histogram & plot: Display a histogram of the delays found and a plot with the detected sound, the marker event and the onset of the sound events. Color codes are green (smallest delay) and red (longest delay).
- Create channel with specific sounds: Create new data channel which contains only marker onsets which could have been assigned to a marker in the specified marker channel (Default: No).

- Channel action: Add will append the new marker channel as additional channel to the specified PsPM file. Replace will overwrite the last marker channel of the PsPM file (be careful with reference markers). (Default: ‘add’)
- Marker channel
- Max delay: Upper limit in seconds of the window in which sounds are accepted to belong to a marker. Default: 3s
- Min delay: Lower limit in seconds of the window in which sounds are accepted to belong to a marker. Default: 0s
- Expected sound count: Checks for correct number of detected sounds. If too few sounds are found, threshold is lowered until specified count is reached.

12 First level

12.1 GLM (modality-independent options)

Related function: `scr_glm`, `scr_glm_recon`, `scr_get_timing`

General linear convolution models (GLM) are powerful for analysing evoked responses in various modalities that follow an event with (approximately) fixed latency. This is similar to standard analysis of fMRI data. The user specifies events for different conditions. These are used to estimate the mean response amplitude per condition. These mean amplitudes can later be compared, using the contrast manager.

Model Filename & output directory

Specify file name and directory where the *.mat file with the resulting model will be written.

Modality specific Channel

Indicate the channel containing the modality specific data. By default the first modality specific channel is assumed to contain the data for this model. If the first modality specific channel does not contain the data for this model (e. g. there are two modality specific channels), indicate the channel number (within the modality specific file) that contains the data for this model.

Time Units

Indicate the time units on which the specification of the conditions will be based. Time units can be specified in ‘seconds’, number of ‘markers’, or number of data ‘samples’. Time units refer to the beginning of the data file and not to the beginning of the original recordings e. g. if data were trimmed.

Option for marker channels:

- **Marker Channel:** Indicate the marker channel. By default the first marker channel is assumed to contain the relevant markers. Markers are only used if you have specified the time units as ‘markers’.

Data & Design

Add the required number of data files or sessions here. These will be concatenated for analysis.

Data File Add the data file containing the modality specific data (and potential marker information). If you have trimmed your data, add the file containing the trimmed data.

Missing Epochs Indicate epochs in your data in which the modality specific signal is missing or corrupted (e.g., due to artifacts). NaN values in the signal will be interpolated for filtering and downsampling and later automatically removed from data and design matrix.

- **No Missing Epochs:** The whole time series will be analyzed (default).
- **Define Missing Epochs:** Define the start and end points of the missing epochs either as epoch files or manually. Missing epochs will be excluded from the design matrix. Start and end points have to be defined in seconds starting from the beginning of the session.
 - **Missing Epoch File:** Indicate an epoch file specifying the start and end points of missing epochs. The mat file has to contain a variable ‘epochs’, which is an $m \times 2$ array, where m is the number of missing epochs. The first column marks the start points of the epochs that are excluded from the analysis and the second column the end points.
 - **Enter Missing Epochs Manually (m: nr. of epochs):** Enter the start and end points of missing epochs manually. Specify an $m \times 2$ array, where m is the number of missing epochs. The first column marks the start points of the epochs that are excluded from the analysis and the second column the end points.

Design Specify the timing of the events within the design matrix. Timing can be specified in ‘seconds’, ‘markers’ or ‘samples’ with respect to the beginning of the data file. See ‘Time Units’ settings. Conditions can be specified manually or by using multiple condition files (i.e., an SPM-style mat file). There are several possibilities to specify the design. All of them require you to state, for each condition:

- Name of the experimental condition

- Onsets: vector of event onsets for this condition, expressed in seconds, marker numbers, or samples, as specified in time units. If seconds, do use precise values according to the data type (e. g. at least 0.1 s time resolution for SCR)
- Durations (optional, default 0): vector of durations of each event for this condition. You need to use 'seconds' or 'samples' as time units
- Parametric modulators: this is used to specify regressors that specify how responses in an experimental condition depend on a parameter to model the effect e.g. of habituation, reaction times, or stimulus ratings. For each parametric modulator a new regressor is included in the design matrix. To create this column, the normalized parameters are multiplied with the respective onset regressors. Parametric modulators require:
 - Names for each parametric modulator for this condition
 - Actual values: a vector for each parameter for this condition, containing as many numbers as there are onsets
 - Polynomial degree. A value of 1 leaves the parametric modulator unchanged and thus corresponds to a linear change over the values of the parametric modulator (first-order). Higher order modulation introduces further columns that contain the non-linear parametric modulators [e.g., second-order: (squared), third-order (cubed), etc].
- Condition File: Create a file with the following variables:
 - names: a cell array of string for the names of all experimental conditions
 - onsets: a cell array of number vectors for the event onsets with the same number of elements as names
 - durations (optional, default 0): a cell array of vectors for the duration of each event
 - pmod (optional): a struct array with the same number of elements as names, and containing the fields
 - * name: cell array of names for each parametric modulator for this condition
 - * param: cell array of vectors for each parameter for this condition, containing as many numbers as there are onsets
 - * poly (optional, default 1): specifies the polynomial degree
 - e.g. produce a simple multiple condition file by typing: `names = {'condition a', 'condition b'}; onsets = {[1 2 3], [4 5 6]}; save('testfile', 'names', 'onsets');`

- Enter conditions manually:
 - Name: Specify the name of the condition.
 - Onsets: Specify a vector of onsets.
 - Durations: Typically, a duration of 0 is used to model an event onset. If all events included in this condition have the same length specify just a single number. If events have different durations, specify a vector with the same length as the vector for onsets.
 - Parametric Modulator(s) [optional] (n: nr. of pmods): If you want to include a parametric modulator, specify a vector with the same length as the vector for onsets.
 1. Name: Specify the name of the parametric modulator.
 2. Polynomial Degree: Specify an exponent that is applied to the parametric modulator.
 3. Parameter Values: Specify a vector with the same length as the vector for onsets.
- No condition - If there is no condition, it is mandatory to specify a nuisance file (e. g. for illuminance GLM, see 11.4).

Nuisance File (optional) You can include nuisance parameters such as motion parameters in the design matrix. Nuisance parameters are not convolved with the canonical response function. This is also used for the illuminance GLM (see 11.4). The file has to be either a .txt file containing the regressors in columns, or a .mat file containing the regressors in a matrix variable called **R**. There must be as many values for each column of **R** as there are data values in your data file. PsPM will call the regressors pertaining to the different columns **R1**, **R2**, ...

Normalize

Specify if you want to z-normalize the modality specific data for each subject. For within-subjects designs, this is highly recommended, but for between-subjects designs it needs to be set to false.

Filter Settings

Specify how you want filter the modality specific data.

Default Standard settings for the Butterworth bandpass filter. These are the optimal settings for the modality specific data.

Edit Settings Create your own filter settings (not encouraged).

- Low-Pass Filter
 - Enable
 1. Cutoff Frequency: Specify the low-pass filter cutoff in Hz.
 2. Filter Order: Specify the low-pass filter order.
 - Disable
- High-Pass Filter
 - Enable
 1. Cutoff Frequency: Specify the high-pass filter cutoff in Hz.
 2. Filter Order: Specify the high-pass filter order.
 - Disable
- New Sampling Rate: Specify the sampling rate in Hz to down sample modality specific data. Enter NaN to leave the sampling rate unchanged.
- Filter Direction {uni, bi}, (default: uni): A unidirectional filter is applied twice in the forward direction. A ‘bidirectional’ filter is applied once in the forward direction and once in the backward direction to correct the temporal shift due to filtering in forward direction.

Overwrite Existing File

Specify whether you want to overwrite existing mat files.

12.2 GLM for SCR

Related function: `scr_glm`, `scr_glm_recon`, `scr_get_timing`

This section only covers modality specific topics for GLM. Settings applying to all modalities are discussed in the general section GLM [12.1]. References: [5, 17, 8, 9].

Basis Function

Basis functions for the peripheral model. Standard is to use a canonical skin conductance response function (SCRf) with time derivative for later reconstruction of the response peak.

SCRf0 SCRf without derivatives.

SCRf1 SCRf with time derivative (default). This is the recommended option based on the publication [9].

SCRf2 SCRf with time and dispersion derivative.

FIR Uninformed finite impulse response (FIR) model: specify the number and duration of time bins to be estimated.

- Arguments
 - N: Number of Time Bins: Number of time bins.
 - D: Duration of Time Bins: Duration of time bins (in seconds).

12.3 GLM for evoked HPR

Related function: `scr_glm`, `scr_glm_recon`, `scr_get_timing`

This section only covers modality specific topics for GLM. Settings applying to all modalities are discussed in the general section GLM[12.1]. References: [29].

Basis Function

Basis functions for the peripheral model.

HPRF_E

- Arguments
 - Number of basis functions

FIR Uninformed finite impulse response (FIR) model: specify the number and duration of time bins to be estimated.

- Arguments
 - N: Number of Time Bins: Number of time bins.
 - D: Duration of Time Bins: Duration of time bins (in seconds).

12.4 GLM for fear-conditioned HPR

Related function: `scr_glm`, `scr_glm_recon`, `scr_get_timing`

This section only covers modality specific topics for GLM. Settings applying to all modalities are discussed in the general section GLM[12.1]. References: [30].

Basis Function

Basis functions for the peripheral model.

Function

HPRF_FC0 HPRF_FC without derivatives.

HPRF_FC1 HPRF_FC with time derivative.

SOA Specify custom SOA for response function. Tested values are 3.5s, 4s and 6s. Default: 3.5s

12.5 GLM for fear-conditioned PSR

Related function: `scr_glm`, `scr_glm_recon`, `scr_get_timing`

This section only covers modality specific topics for GLM. Settings applying to all modalities are discussed in the general section GLM[12.1]. References: [35].

Basis Function

Basis functions for the peripheral model.

PSRF_FC0 PSRF_FC with CS only and without derivatives.

PSRF_FC1 PSRF_FC with CS and derivatives for CS (default).

PSRF_FC2 PSRF_FC with CS and US. Without derivatives.

PSRF_FC3 PSRF_FC with US only and without derivatives.

Default Channel

Left eye default Look for left eye default channels.

Right eye default Look for right eye default channels.

12.6 GLM for evoked RAR

Related function: `scr_glm`, `scr_glm_recon`, `scr_get_timing`

This section only covers modality specific topics for GLM. Settings applying to all modalities are discussed in the general section GLM[12.1]. References: [40].

Basis Function

Basis functions for the peripheral model.

RARF_E0 RARF_E without time derivative.

RARF_E1 RARF_E with time derivative (default).

12.7 GLM for fear-conditioned RAR

Related function: `scr_glm`, `scr_glm_recon`, `scr_get_timing`

This section only covers modality specific topics for GLM. Settings applying to all modalities are discussed in the general section GLM[12.1]. References: .

Basis Function

Basis functions for the peripheral model.

RARF_FC0 RARF_FC early and late response.

RARF_FC1 RARF_FC early response with derivative.

12.8 GLM for evoked RPR

Related function: `scr_glm`, `scr_glm_recon`, `scr_get_timing`

This section only covers modality specific topics for GLM. Settings applying to all modalities are discussed in the general section GLM[12.1]. References: [40].

Basis Function

Basis functions for the peripheral model.

RPRF_E0 RPRF_E without time derivative.

RPRF_E1 RPRF_E with derivative.

12.9 GLM for evoked RFRR

Related function: `scr_glm`, `scr_glm_recon`, `scr_get_timing`

This section only covers modality specific topics for GLM. Settings applying to all modalities are discussed in the general section GLM[12.1]. References: [40].

Basis Function

Basis functions for the peripheral model.

RFRRF_E0 RFRRF_E without time derivative.

RFRRF_E1 RFRRF_E with derivative.

12.10 Non-Linear Model for SCR

Related function: `scr_dcm`, `scr_dcm_inv`

Non-linear models for SCR are powerful if response timing is not precisely known and has to be estimated. A typical example are anticipatory SCR in fear conditioning – they must occur at some point within a time-window of several seconds duration, but that time point may vary over trials. Dynamic causal modelling (DCM) is the framework for parameter estimation. PsPM implements an iterative trial-by-trial algorithm. Different from GLM, response parameters are estimated per trial, not per condition, and the algorithm must not be informed about the condition. Trial-by-trial response parameters can later be summarized across trials, and compared between conditions, using the contrast manager. References: [22, 10]

Model Filename & Output directory

Specify file name for the resulting model. Specify directory where the mat file with the resulting model will be written.

SCR channel

Indicate the channel containing the SCR data. By default the first SCR channel is assumed to contain the data for this model. If the first SCR channel does not contain the data for this model (e. g. there are two SCR channels), indicate the channel number (within the SCR file) that contains the data for this model.

Data & design

Add the appropriate number of data files or sessions here. Results will be concatenated.

Data File Add the data file containing the SCR data. If you have trimmed your data, add the file containing the trimmed data.

Design Specify the timings of individual events from your design either by creating a timing file or by entering the timings manually. The DCM framework allows you to specify two types of events:

Fixed latency (evoked): An event is assumed to elicit an immediate response. The amplitude of the sympathetic arousal will be estimated, while the latency and duration of the response are fixed. This event type is meant to model evoked responses.

Flexible latency and duration (event-related): An event is assumed to elicit sympathetic arousal within a known response window, but with unknown amplitude, latency and duration. For each event of this type, specify a time window in which the response is expected. PsPM will then estimate the amplitude, duration and latency of the response. An example for this type of event is an

anticipatory response which might vary in timing between trials (e. g. in fear conditioning).

- **Timing File:** The timing file has to be a .mat file containing a cell array called 'events'. For a design with n trials and m events per trial ($n \times m$ events in total), the cell array has to be structured in the following way: Create m cells in the cell array (one per event type that occurs in each trial). Each cell defines either a fixed or a flexible event type. A cell that defines a fixed event type has to contain a vector with n entries, i.e. one time point per trial, in seconds, samples or markers. A cell that defines a flexible type has to contain an array with n rows and two columns. The first column specifies the onsets of the time windows for each trial, while the second column specifies the offsets of the time windows. It is assumed that all trials have the same structure, i.e. the same number of fixed and flexible event types. For individual trials with a different structure you can enter negative values as time information to omit estimation of a response. For later comparison between trials of different conditions, it is absolutely mandatory that they contain the same types of events, to avoid bias. Hence, if one condition omits an event (e. g. unreinforced trials in conditioning experiments), the omitted event needs to be modelled as well.
- **Enter Timing Manually:** In the DCM framework, a session is structured in n individual trials. Each trial contains m fixed and/or flexible event types. All trials need to have the same structure. Create event types to define the structure of a trial and enter the timings for all events.
 - **Name (optional):** Enter a name of the event. This name can later be used for display and export.
 - **Onsets:** For events with a fixed response, specify a vector of onsets. The length of the vector corresponds to the number of trials (n). For events with a flexible response, specify a two column array. The first column defines the onset of the time window in which the response occurs. The second column defines the offset. The number of rows of the array corresponds to the number of trials (n). All timings are specified in seconds.

Condition names (optional) Specify the conditions that the individual trials belong to. This information is not used for the parameter estimation, but it allows you to later access the conditions in the contrast manager.

- **Name:** Specify the name of the condition.
- **Index:** Specify a vector of trial indices between 1 and n . The length of the vector corresponds to the number of events included in this condition.

Data Options

Normalization Specify if you want to normalize the SCR data for each subject. For within-subjects designs, this is highly recommended. During analysis,

data are always z-transformed, but the parameter estimates are transformed back if this is set to false.

Filter Settings Specify if you want filter the SCR data.

- Default: Standard settings for the Butterworth bandpass filter. These are the optimal settings from [10]: bidirectional Butterworth band pass filter with cutoff frequencies of 0.0159 Hz and 5 Hz, downsampling to 10 Hz.
- Edit Settings: Create your own filter (discouraged).
 - Low-Pass Filter
 1. Enable
 - Cutoff Frequency: Specify the low-pass filter cutoff in Hz.
 - Filter Order: Specify the low-pass filter order.
 2. Disable
 - High-Pass Filter
 1. Enable
 - Cutoff Frequency: Specify the high-pass filter cutoff in Hz.
 - Filter Order: Specify the high-pass filter order.
 2. Disable
- New Sampling Rate: Specify the sampling rate in Hz to down sample SCR data. Enter NaN to leave the sampling rate unchanged.
- Filter Direction {uni, bi}, (default: bi): A unidirectional filter is applied twice in the forward direction. A 'bidirectional' filter is applied once in the forward direction and once in the backward direction to correct the temporal shift due to filtering in forward direction.

Response Function Options

Estimate the Response Function from The Data A response function can be estimated from the data and used instead of the canonical response function (default 0 for fully flexible and 1 for fix and flex/fix paradigms). This is not normally recommended unless you have long inter trial intervals in the range of 20-30 s [10].

Only Estimate RF (Do Not Do Trial-Wise DCM) This option can be used to estimate an individual response function to be used in analysis of another experiment.

Call External File to Provide Response Function Call an external file to provide a response function, which was previously estimated using the option "only estimate RF".

Inversion Options

Number of Trials to Invert at The Same Time (default: 2 s) The iterative DCM algorithm accounts for response overlap by considering several trials at a time. This can be set here.

SF-Free Window Before First Event [s] (default: 2 s) The DCM algorithm automatically models spontaneous fluctuations in inter trial intervals. Here, you can define a time window before the first event in every trial in which no spontaneous fluctuation will be estimated.

SF-Free Window After Last Event [s] (default: 5 s) The DCM algorithm automatically models spontaneous fluctuations in inter trial intervals. Here, you can define a time window after the last event in every trial in which no spontaneous fluctuation will be estimated.

Maximum Frequency of SF in ITIs [Hz] (default: 0.5 Hz) The DCM algorithm automatically models spontaneous fluctuations in inter trial intervals. Here you can define the minimal delay between two subsequent spontaneous fluctuations.

SCL-Change-Free Window Before First Event [s] (default: 2 s) The DCM algorithm automatically models baseline drifts in inter trial intervals. Here, you can define a window before the first event in every trial in which no change of the skin conductance level will be assumed.

SCL-Change-Free Window After Last Event [s] (default: 5 s) The DCM algorithm automatically models baseline drifts in inter trial intervals. Here, you can define a window after the last event in every trial in which no change of the skin conductance level will be assumed.

Display Options

Display Progress Window Show a on-line diagnostic plot for each iteration of the estimation process.

Display Intermediate Windows Show small plots displaying the progress of each iteration in the estimation process.

12.11 SF models

Related function: `scr_sf`

This suite of models is designed for analysing spontaneous fluctuations (SF) in skin conductance as a marker for tonic arousal. SF are analysed over time windows that typically last 60 s and should at least be 15 s long. PsPM implements 3 different models: (1) Skin conductance level (SCL): this is the mean

signal over the epoch (2) Area under the curve (AUC): this is the time-integral of the above-minimum signal, divided by epoch duration. This is designed to be independent from SCL and ideally represents the number \times amplitude of SF in this time window. (3) Number of SF estimated by DCM (Dynamic Causal Modelling) or MP (Matching Pursuit): this is a non-linear estimation of the number of SF, and is the most sensitive indicator of tonic arousal. It relies on absolute data values as it implements an absolute threshold for data peaks. References: [24, 25].

The parameter estimates of these different methods have interpretable physical units: (1) SCL parameters have the same units as the input data, most often μS , (2) AUC parameters have the same units as the input data, most often μS , and (3) DCM and MP parameters are the frequency of above-threshold SF, stated in $Hz = 1/s$.

Data File

Add the data file containing the SCR data (and potential marker information). If you have trimmed your data, add the file containing the trimmed data.

Model Filename & Output directory

Specify file name for the resulting model. Specify directory where the mat file with the resulting model will be written.

Method

Choose the method for estimating tonic sympathetic arousal: AUC (equivalent to number \times amplitude of spontaneous fluctuations), SCL (tonic skin conductance level), DCM or MP. The latter two estimate the number of spontaneous fluctuations, requiring absolute data units as both methods implement an absolute amplitude threshold. In theory, DCM provides highest sensitivity but is slow [24]. MP is a very fast approximation to the DCM results, and comparable in sensitivity for analysis of empirical data [25]. In simulations, it is less accurate when the expected number of SF exceeds 10/min.

Time Units

Indicate the time units on which the specification of the conditions will be based. Time units can be specified in 'seconds', number of 'markers', or number of data 'samples'. Time units refer to the beginning of the data file and not to the beginning of the original recordings e. g. if data were trimmed. Choose 'seconds', 'markers', 'samples', or 'whole' to analyse the entire data file as one epoch.

Seconds/Markers/Samples

- Epochs - define data epochs to analyse
 - Epoch File
 - Enter Epochs Manually

Markers

- Marker Channel (default: 0): Indicate the marker channel. By default the first marker channel is assumed to contain the relevant markers. Markers are only used if you have specified the time units as ‘markers’.

Filter Settings

Specify if you want filter the SCR data.

Default Standard settings for the Butterworth bandpass filter: unidirectional Butterworth bandpass filter with cut off frequencies of 0.0159 Hz and 5 Hz, down sampling to 10 Hz.

Edit Settings Create your own filter (discouraged).

- Low-Pass Filter
 - Enable
 1. Cutoff Frequency: Specify the low-pass filter cutoff in Hz.
 2. Filter Order: Specify the low-pass filter order.
 - Disable
- High-Pass Filter
 - Enable
 1. Cutoff Frequency: Specify the high-pass filter cutoff in Hz.
 2. Filter Order: Specify the high-pass filter order.
 - Disable
- New Sampling Rate: Specify the sampling rate in Hz to down sample SCR data. Enter NaN to leave the sampling rate unchanged.
- Filter Direction): A unidirectional filter is applied twice in the forward direction. A ‘bidirectional’ filter is applied once in the forward direction and once in the backward direction to correct the temporal shift due to filtering in forward direction.

Channel

Indicate the channel containing the SCR data. By default the first SCR channel is assumed to contain the data for this model. If the first SCR channel does not contain the data for this model (e. g. there are two SCR channels), indicate the channel number (within the SCR file) that contains the data for this model.

Overwrite Existing File

Specify whether you want to overwrite existing mat file.

Threshold (used for DCM and MP only)

Threshold for SN detection - default 0.1 μ S.

Display Progress Window (used for DCM and MP only)

Show a on-line diagnostic plot for each iteration of the estimation process (DCM) or for the result of the estimation process (MP).

Display Intermediate Windows (used for DCM only)

Show small plots displaying the progress of each iteration in the estimation process.

12.12 Review First-Level Model (via Batch editor)

Related function: `scr_review`

This module allows you to look at the first-level (within-subject) model to investigate model fit and potential estimation problems. This is not necessary for standard analyses. Further processing can be performed directly on the second level after first-level model estimation.

Model File

Choose model file to review.

Model Type

Specify the type of model.

GLM Specify the plot that you wish to display:

- Design matrix
- Orthogonality
- Predicted & Observed

- Regressor names
- Reconstructed

Non-linear model

- Inversion results for one trial: Non-linear SCR model (DCM) - Review individual trials or sequences of trials inverted at the same time.
 - Session Number (Default 1): Data session. Must be 1 if there is only one session in the file.
 - Trial Number: Trial to review.
- Predicted & Observed for all trials: Non-linear SCR model for event-related responses - Review summary plot of all trials.
 - Session Number
 - Figure Name [optional]: Adding a figure name saves the figure as .fig file.
- SCRF: Non-linear model for event-related responses - review SCRF (useful if SCRF was estimated from the data).

SF Non-linear model for spontaneous fluctuations: Show inversion results for one episode

- Epoch Number: Epoch to review.

Contrasts Display contrast names for any first level model.

12.13 First-Level Model Review Manager (via GUI)

Related function: `scr_review`

Display information stored in a model file through an easily accessible interface. Add a model file to the menu via *Add Models*. Available content of a highlighted model is listed on the right hand side under *Figure Selection*. For non-linear models, you can select the session number by entering its index in the field *Session number*; GLMs are inverted and displayed across all sessions. Click on any *Display* or *Show* button to visualize information. Details for each model type are listed in Chapter 12.12.

12.14 First-Level Contrasts (via Batch editor)

Related function: `scr_con1`

Define within-subject contrasts here for testing on the second level. Contrasts can be between conditions (GLM), epochs (SF) or trials (Non-linear SCR models). Contrast weights should add up to 0 (for testing differences between

conditions/epochs/trials) or to 1 (for testing global/intercept effects across conditions/epochs/trials). Example: an experiment realises a 2 (Factor 1: a, A) x 2 (Factor 2: b, B) factorial design and consists of 4 conditions: aa, aB, Ab, AB. Testing the following contrasts is equivalent to a full ANOVA model: Main effect factor 1: $[1\ 1\ -1\ -1]$, Main effect factor 2: $[1\ -1\ 1\ -1]$, Interaction factor 1 x factor 2: $[1\ -1\ -1\ 1]$. To test condition effects in non-linear models, assign the same contrast weight to all trials from the same condition.

Model File(s)

Specify the model file for which to compute contrasts.

Specify Contrasts on Datatype

Contrasts are usually specified on parameter estimates. For GLM, you can also choose to specify them on conditions or reconstructed responses per condition. In this case, your contrast vector needs to take into account only the first basis function. For non-linear SCR models, you can specify contrasts based on conditions as well. This will average within conditions. Use the review manager to extract condition names and their order. This argument will be ignored for other first-level models.

- Parameter: Use all parameter estimates.
- Condition: Contrasts formulated in terms of conditions in a GLM, automatically detects number of basis functions and uses only the first one (i.e. without derivatives), or based on assignment of trials to conditions in DCM.
- Reconstructed: Contrasts formulated in terms of conditions in a GLM, reconstructs estimated response from all basis functions and uses the peak of the estimated response.

Contrast(s)

Contrast Name This name identifies the contrast in tables and displays.

Contrast Vector This is a vector on all included conditions (GLM), trials (non-linear SCR model for event-related responses), or epochs (non-linear model for SF). Shorter vectors will be appended with zeros. To specify a condition or trial difference, the contrast weights must add up to zero (e. g. was sympathetic arousal in condition A larger than in condition B: $c = [1\ -1]$). To specify a summary of conditions or trials, the contrast weights should add up to 1 to retain proper scaling (e. g. was non-zero sympathetic arousal elicited in combined conditions A and B: $c = [0.5\ 0.5]$).

Delete Existing Contrasts

Deletes existing contrasts from the model file.

12.15 First level contrast manager (via GUI)

Related function: `scr_con1`

The Manager guides you through the setup of pre-defined within-subject contrasts applied to the parameter estimates of your model.

Load Model Import a model file from a subject containing parameter estimates for which to compute contrasts.

Define Contrast Name Enter a name to identify a contrast. By pressing *New Contrast*, the contrast is added to the box *Contrasts*. You can reset existing contrasts by highlighting a contrast and pressing *Clear Contrast* or you can remove contrasts from your model file by pressing *Delete Contrast*.

Define Stats Type Depending on the model (GLM, spontaneous fluctuation or non-linear model), different data types are available (see Chapter 12.14 for details). Choose the type you want to be entered into a statistical test.

Define Test Three pre-defined types of statistics can be computed on your estimates. Parameter estimates for individual conditions or trials are grouped by the user to compute test contrasts. “Group” refers to groups of conditions/trials, not to groups of individuals or datasets. After choosing the test, you can add or remove conditions/trials to a group by clicking on them in the *Names* window. The color will indicate to which group they belong.

- Test of intercept: Compute the average of conditions entered in *Group 1*. This option is suitable if you are interested in the main effect of one or across several conditions.
- Test of condition differences: Compute the difference between the averages of conditions/trials in *Group 1* and conditions/trials *Group 2*.
- Test of quadratic effects: Here you compute the combined effect of *Group 1* and *Group 3* against *Group 2*. This option requires at least three conditions/trials.

Run Execute computation of statistics. The contrasts are stored in your model files and can be reviewed any time using the Review Manager (Chapter 12.13).

12.16 Export Statistics

Related function: `scr_exp`

Export first level statistics to a file for further analysis in statistical software, or to the screen.

Model File(s)

Specify file from which to export statistics.

Stats type

Normally, all parameter estimates are exported. For GLM, you can choose to only export the first basis function per condition, or the reconstructed response per condition. For DCM, you can specify contrasts based on conditions as well. This will average within conditions. This argument cannot be used for other models.

- Parameter: Export all parameter estimates.
- Condition: Export all conditions in a GLM, automatically detects number of basis functions and export only the first one (i.e. without derivatives), or export condition averages in DCM.
- Reconstructed: Export all conditions in a GLM, reconstructs estimated response from all basis functions and export the peak of the estimated response.

Target

Export to screen or to file?

Delimiter for Output File

Select a delimiter for the output file. Default is 'tab', you can select from a choice of several options or specify as free text.

13 Second level

13.1 Define Second-Level Model

Related function: `scr_con2`

Define one-sample and two-sample t-tests on the between-subject (second) level. A one-sample t-test is normally used to test within-subject contrasts and is equivalent to t-contrasts in an ANOVA model. A two-sample t-test is required for between-subjects contrasts or interactions. This module sets up the model but does not report results.

Test Type

Specify the test type.

One Sample T-Test

- Model File(s)

Two Sample T-Test

- Model File(s) 1: Model files for group 1.
- Model File(s) 2: Model files for group 2.

Output directory

Specify directory where the mat file with the resulting model will be written.

Filename for Output Model

Specify name for the resulting model.

Define Contrasts

Define which contrasts to use from the model files, and the second level contrast names. Names can be read from the first model file, or just be numbered.

Read from First Model File

- All Contrasts
- Contrast Vector: Index of first-level contrasts to use.

Number Contrasts

- All Contrasts
- Contrast Vector: Index of first-level contrasts to use.

Overwrite Existing File

Specify whether you want to overwrite existing mat file.

13.2 Report Second-Level Results

Related function: `scr_rev2`

Result reporting for second level model.

Model File

Specify 2nd level model file.

Contrast Vector (only accessible from Batch Editor)

Index of contrasts to be reported (optional).

14 Tools

14.1 Display Data

Related function: `scr_display`

Display PsPM data file in a new figure.

Data File

Specify data file to display.

14.2 Data editor

Related function: `scr_data_editor`

The data editor allows you to visualize data time series and mark epochs, for example to mark artefacts that should be excluded, for example to be used as missing epochs in GLM (see 12.1).

Startup

The Data editor can be started from the PsPM window, the Matlabbatch and from the Matlab command line. The command line startup requires the PsPM folder to be added to the Matlab path. Once that is done, the data editor can be started by typing '`scr_data_editor(argument)`' in the Matlab command line. The command accepts two types of arguments. (i) a path to file, which causes the editor to open the specified file and to work in the '**file mode**' or (ii) a data vector which causes the editor to plot the passed data vector and to work in the '**inline mode**'. If no argument is specified, the editor is started in 'file mode'.



Data modes

The data editor differs between two data modes. The data mode depends on the specified startup argument.


File mode Is entered when called from the PsPM window, the Matlabbatch or a file path or no argument is specified at command line startup. File input/output settings as well as the Channel view are visible on the left. The latter can be used to select the plotted channel. Multiple selection is possible and the color of the plot corresponds to the color in the channel list. File input settings can be used to change the file to be edited, while the output settings specify where the edited data should be stored to.


Inline mode Is entered when a data vector is specified as command line startup argument. Channel view and file input/output settings are hidden. Once the user exits, the editor returns either the interpolated data or the selected epochs in a PsPM epoch format.


Data navigation

Data navigation can be done by zooming () and panning (). Zooming does only change the horizontal axis. After zooming axis limits remain fixed when changing the selected channel. This sometimes may cause data not to be plotted because the data points are out of the visible range. Zooming out will make the data appear again. Panning allows the rearrangement of the plot horizontally and vertically. After panning the axis limits remain fixed as well and data may disappear when changing the selected channel.

Epochs

Add epochs New epochs can be added by clicking the 'add epoch' button (). Once clicked the cursor will change to a crosshair and it is possible to select data in the plot, which will upon release create a new epoch in the selected range. The new epoch will appear on the right side in the epoch list and is marked in green on the plot.

Remove epochs Existing epochs can be removed by clicking the 'remove epoch' button (). Once clicked the cursor will change to a crosshair and it is possible to select the range in which the epochs should be removed. If an epoch is selected partially, the rest of the epoch will remain. The epoch-list on the right side will be updated automatically.

Epoch navigation In order to navigate between epochs it is either possible to use the epoch list on the right side or the two epoch navigation buttons (). The selected epoch always corresponds to the selected epoch in the epoch-list and is marked in black in the plot.

Output format

There are two possible output formats. The output, depending on the data mode, will either be written to a specified output file (file mode) or will be returned as a data vector (first argument; inline mode).

Epochs If epochs is selected, the output will be a $n \times 2$ vector, where n is the number of epochs. The first column marks the onset of the epoch, while the second column marks the offset of the epoch. The time unit is seconds. In file mode the data will be written into the specified mat file in the variable 'epochs'.

Interpolated data If interpolated data is selected, the output will be the specified data itself with the selected channels (in Channel view) interpolated during the selected epochs. In file mode the original channels will be replaced. If 'Display interpolated curve' is checked the interpolated data will be displayed in the plot as a dashed line.

Matlabbatch

Possible options when the Data editor is started from Matlabbatch.

Data file Specify the PsPM datafile to be edited.

14.3 Rename File

Related function: `scr_ren`

Rename PsPM data file. This renames the file and updates the file information.

File

Choose how many files to rename.

File Name Choose name of original file.

New File Name Choose new file name.

14.4 Split Sessions

Related function: `scr_split_sessions`

Split sessions, defined by trains of markers. This function is most commonly used to split fMRI sessions when a (slice or volume) pulse from the MRI scanner has been recorded. The function will identify trains of markers and detect breaks in these marker sequences. The individual sessions will be written to new files with a suffix `'_sn'`, and the session number. You can choose a marker channel if several were recorded.

Data File

Choose the data file, in which you want to split sessions.

Marker Channel

If you have more than one marker channel, choose the marker channel used for splitting sessions (default: use first marker channel).

- Default
- Number

Overwrite Existing File

Choose “yes” if you want to overwrite existing file(s) with the same name.

14.5 Merge files

Related function: `scr_merge`

Allows to merge a second into a first file. Multiple files are allowed and are processed in a sequential manner. Which means the first element of second file is merged into the first element of first file and so on. Therefore first file and second file must have the same number of elements. The files are aligned according to the first event of a given marker channel or to the start of the file. The output file consists of an 'm' at the beginning and the name of the first file appended.

Datafiles

Specify the PsPM datafiles to be merged.

First file(s) Specify the first of the two files to be merged. This can be one file or a set of files. The output file will have the name of the first file prepended with an 'm'.

Second file(s) Specify the second of the two files to be merged. This can be one file or a set of files. This set must have the same length as the set defined as first file(s).

Reference

Specify whether to align the files with respect to the first marker or with respect to the file start.

Options

Marker channel Specify for each file (first and second) a channel which should be used as marker reference. A 1x2 vector is expected. If equal to 0, the first marker channel is used. Default: [0 0]

Overwrite existing file(s) Specify whether existing files should be overwritten (Yes) or not (No). Default: No

14.6 Artifact Removal

Related function: `scr_pp`

This module offers a few basic artifact removal functions. Currently, a median filter and a Butterworth low pass filter are implemented. The median filter is useful to remove short "spikes" in the data, for example from gradient switching in MRI. The Butterworth filter can be used to get rid of high frequency noise that is not sufficiently filtered away by the filters implemented on-the-fly during first level modelling.

Data File

Choose the data file.

Channel Number

Select the channel to work on.

Filter Type

Currently, median and Butterworth filters are implemented. A median filter is recommended for short spikes, generated for example in MRI scanners by gradient switching. A Butterworth filter is applied in most models; check there to see whether an additional filtering is meaningful.

Median Filter

- Number of Time Points: Number of time points over which the median is taken.

Butterworth Low pass Filter

- Cutoff Frequency: Cutoff frequency has to be at least 20Hz.

Overwrite Existing File

Choose “yes” if you want to overwrite existing file(s) with the same name.

14.7 Downsample Data

Related function: `scr_down`

This function downsamples individual channels in a PsPM file to a required sampling rate, after applying an anti-aliasing Butterworth filter at the Nyquist frequency. The resulting data will be written to a new .mat file, prepended with 'd', and will contain all channels – also the ones that were not downsampled.

Data File

Name of the data files to be downsampled.

New Frequency

Required sampling frequency.

Channels To Downsample

Vector of channels to downsample, or all channels.

Overwrite Existing File

Choose “yes” if you want to overwrite existing file(s) with the same name.

14.8 Interpolate missing data

Related function: `scr_interpolate`

The function interpolates missing values, either for all continuous channels in a specified PsPM data file (file mode), or for selected channel(s) only (channel mode). In file mode, the function writes all channels to a new file with the same name prepended by an ‘i’. In channel mode, the function interpolates data and either replaces a channel or writes the data to a new channel.

Data file

Select data files.

Work mode

Specify whether to work on a whole file or just on the specified channel(s). If whole file is specified, the data will be written to a new file with the same name prepended by an ‘i’. Otherwise the specified channel(s) will be written to a new channel or replace an existing channel in the same file.

- File mode
 - Overwrite existing file: Choose “yes” if you want to overwrite existing file(s) with the same name (Default: No).
- Channel mode
 - Interpolate channel(s): Specify which channel(s) should be interpolated.
 - Mode: Specify how to behave with the interpolated data.
 - * New channel: Always add as a new channel.
 - * Replace channel: Replace specified channel(s).

14.9 Extract segments

Related function: `scr_extract_segments`

This function extracts data segments (e.g., for visual inspection of mean responses per condition).

Mode

Either extract all information from a GLM model file or define the relevant information manually.

Automatically read from GLM Extracts all relevant information from a GLM file.

- GLM file: Choose GLM file to extract the required information.

Manual Specify all the settings manually.

- Data files: PsPM files from which data segments should be extracted.
- Channel: Channel in specified data file from which the segments should be extracted.
- Conditions:
 - Condition files: Should be in the format of the conditions defined in a GLM model. Required fields are names, onsets, duration.
 - Enter conditions manually: Specify the conditions that you want to include in your design matrix.
 - * Name: Specify the name of the condition.
 - * Onsets: Specify a vector of onsets. The length of the vector corresponds to the number of events included in this condition. Onsets have to be indicated in the specified time unit ('seconds', 'samples').
 - * Duration: Specify the length of the condition.

Options

Change values of optional settings.

Timeunit The timeunit in which conditions should be interpreted.

- Seconds
- Samples

Segment length Length of segments. If set (= enabled) durations in conditions will be ignored (-1 = disabled).

Output

Output settings.

Output file Where to store the extracted segments.

- File path: Path to file.
- File name: Name of file.

Overwrite existing file Overwrite existing segment files.

Plot Plot means over conditions with standard error of the mean.

14.10 Segment mean

This function creates means over extracted data segments (as extracted in ‘Extract segments’).

Segment files

Specify the segment files which have been created with the ‘extract segment’ function.

Output file

Where to store the segment mean across the specified files.

File path Path to file.

File name Name of file.

Adjust method

How to deal with different sample rates across segment files. ‘interpolate’ data segments to highest or ‘downsample’ data segments to lowest sampling rate.

Overwrite existing file

Overwrite existing segment mean files.

Plot

Plot means over segment files with standard error of the mean.

14.11 Extract event marker info

Allows to extract additional marker information for further processing. The information can be used to distinguish between different types of events or for other purposes. This is usually used to extract marker information from EEG-style data files such as BrainVision or NeuroScan.

Data file

Specify the PsPM datafile containing a marker channel with a markerinfo field.

Marker channel

Specify which marker channel should be used for marker info extraction.

Output

File Specify the output file to which the marker info should be written to.

Overwrite existing file Overwrite existing marker info files.

15 Troubleshooting and known problems

15.1 Path

If the PsPM folder is added to the path with all subfolders, the batch editor will not work. Only put the PsPM main folder (containing the function `pspm.m`) to the path.

15.2 Diagnostic graphics for non-linear model inversion

During non-linear model inversion, a diagnostic window is displayed for each trial. Between two trials, there is a short period of time during which several tabs appear in that window. If you click on one of the hidden tabs, model inversion will fail due to a display error.

Diagnostic plots do not work in Matlab versions 2014 and upwards. This is due to a limitation of an external software. We are working on a fix.

15.3 Export statistics into text format with tab delimiter

The tab delimiter in the exported files is not correctly interpreted by text editors like MS Word. Nonetheless, the data can be imported into softwares such as Excel or SPSS.

Part III

Tutorial

Contributed by Christoph Korn & Matthias Staib.

16 GLM for SCR tutorial: Appraisal data

Here, we analyze SCR data using a general linear model (GLM). The example data set comprises SCR data from 15 participants and can be downloaded from https://sourceforge.net/projects/pspm/files/Tutorial_dataset_GLM.zip/download.

Results from this data set have been previously published [8, 9]. Each participant saw 45 neutral and 45 aversive pictures within one session that included two short breaks. SCR data were recorded using a 0.5 V coupler, optical (wave to pulse) transducer, and CED Spike, with a minimum sampling rate of 100 Hz.

16.1 Import

We import the SCR data and the corresponding marker data. We first import data from one subject.

- In the batch editor go to *PsPM* → *Data Preparation* → *Import*.
- Specify the Data Type. Several data formats are available. The current data set is in the smr format.
- Select the SCR Data File of the first subject `trsp_1_25.smr`.
- Specify the *Channels*. We need one SCR channel and one marker channel.
 - The *Channel Number* of the SCR channel is 2.
 - For the *Transfer Function* choose *None*.
 - For the *Channel Number* of the marker channel put in *Search* to test the automatic search (otherwise you can specify the number of the marker channel manually. In this data set, the marker channel is 6).

See Figure 16.1 for a picture of the final batch editor. We recommend saving the batch and script so that you can easily re-run your analyses at a later time point (see Chapter 18). Run the batch. A mat file with the name `scr_trsp_1_25.mat` will be created in the same folder as the original data file.

You can have a look at the imported data by loading this file into MATLAB. The cell array data contains two structures. The first one contains the SCR data and the second one the marker data (this data set contains 96 markers).

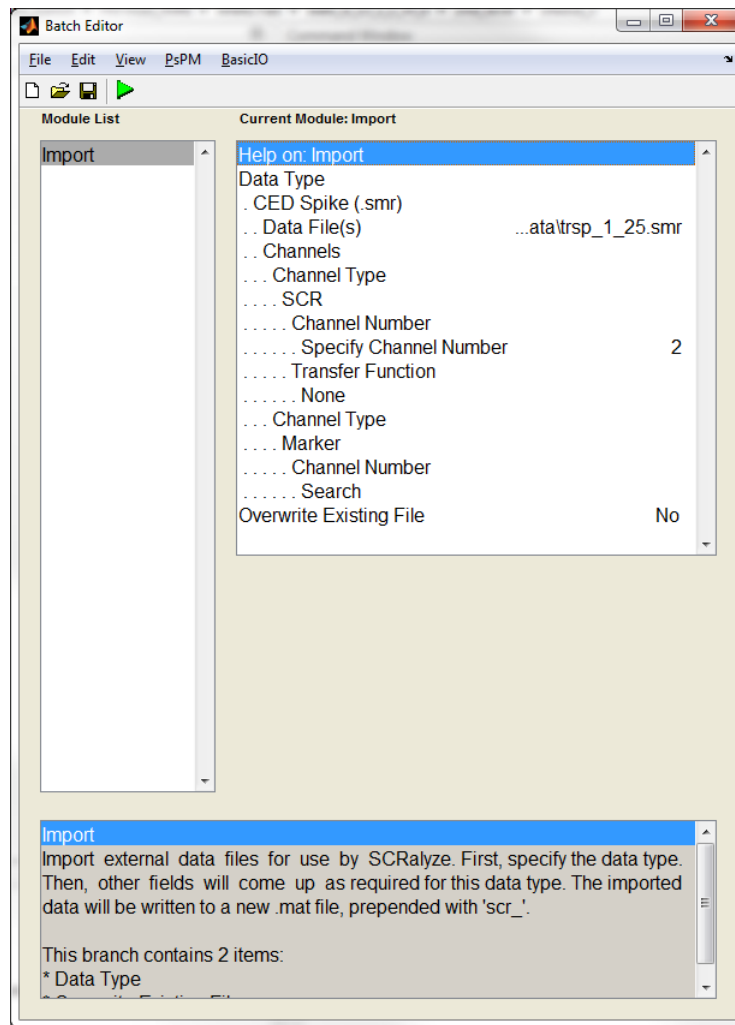


Figure 16.1: Batch editor for importing raw SCR data.

16.2 Trim

Most of the time, the SCR recording is switched on some time before the actual experiment starts and is switched off some time after it ends. These parts of the time series may contain large artifacts from subject motion, setting up the equipment, etc. Trimming excludes these parts from the analyses.

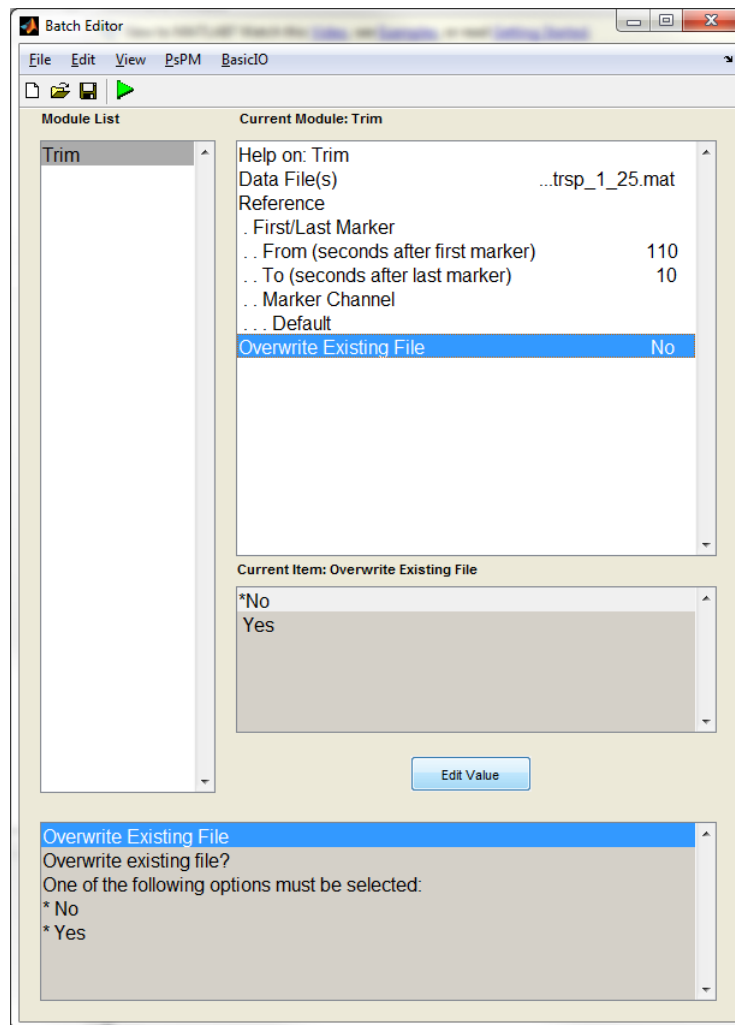


Figure 16.2: Batch editor for trimming SCR data.

- In the batch editor go to *PsPM* → *Data Preparation* → *Trim*.
 - Select the currently imported file as Data File. Alternatively, you can use the *Dependency* button.
- You can choose different References to specify how data should be trimmed. Here, select *First/Last Marker* and
 - *From (seconds after first marker)*: +110 (In the current data set the first 2 minutes are a task-relevant baseline period and are thus trimmed. Note that a positive number will delete at least the first

marker of the original data. Thus, make sure that a possible specification of the First-Level takes this into account.)

- *To (seconds after first marker):* 10 (The specified time window should be large enough to completely include the last trial.)

You can also specify time points before the markers by using negative numbers (see above). See Figure 16.2 for a picture of the final batch editor. Again, it is recommended to save the batch and script for future use. Run the batch. A mat file with the name `tscr_trsp_1_25.mat` will be created (i.e., a “t” will be prepended).

16.3 First-Level

Now, we specify the GLM on the first (i.e., the subject-specific) level, estimating average responses per experimental condition (this equivalent to averaging responses over trials in classical “peak scoring” analysis, or to performing a first level analysis in SPM).

- In the batch editor go to *PsPM* → *First Level* → *SCR* → *GLM*.
- *Model Filename:* This is the name of the resulting mat file containing the GLM. Here, we call it `glm_25`.
- *Output Directory:* The resulting mat file containing the GLM will be saved in this folder.
- *Time Units* on which the specification of the conditions will be based. Here, we want to analyze with respect to Markers.
- *Session(s):* Similar to SPM, SCRalyze allows the specification of multiple sessions per subject. Here, we only have one session.
 - Add the trimmed data (`tscr_trsp_1_25.mat`) as Data File. Alternatively, you can use the *Dependency* button.
 - *Missing Epochs* allows the specification of time periods which you do not want to include in the analysis for example because they contain corrupted data. In the example data set, there are no missing epochs.
 - *Data & Design:* This option allows specifying the different conditions of the experiment. You need to provide the information when the different conditions started. This time information has to be in the unit specified above (see *Time Units*). In the current data set, condition information is provided in Markers and is stored in the mat file `trSP_appraisal_01_25_onsets_1.mat`, which you should select as *Condition File*. When you open this file in MATLAB, you will see that the file contains a 1x3 cell “names” and a 1x3 cell “onsets” specifying three conditions. The numbers in “onsets” correspond to the *n*th marker when the respective trial started.

- *Nuisance File* allows the inclusion of nuisance confounds such as motion or respiration parameters. Here, we leave it empty.

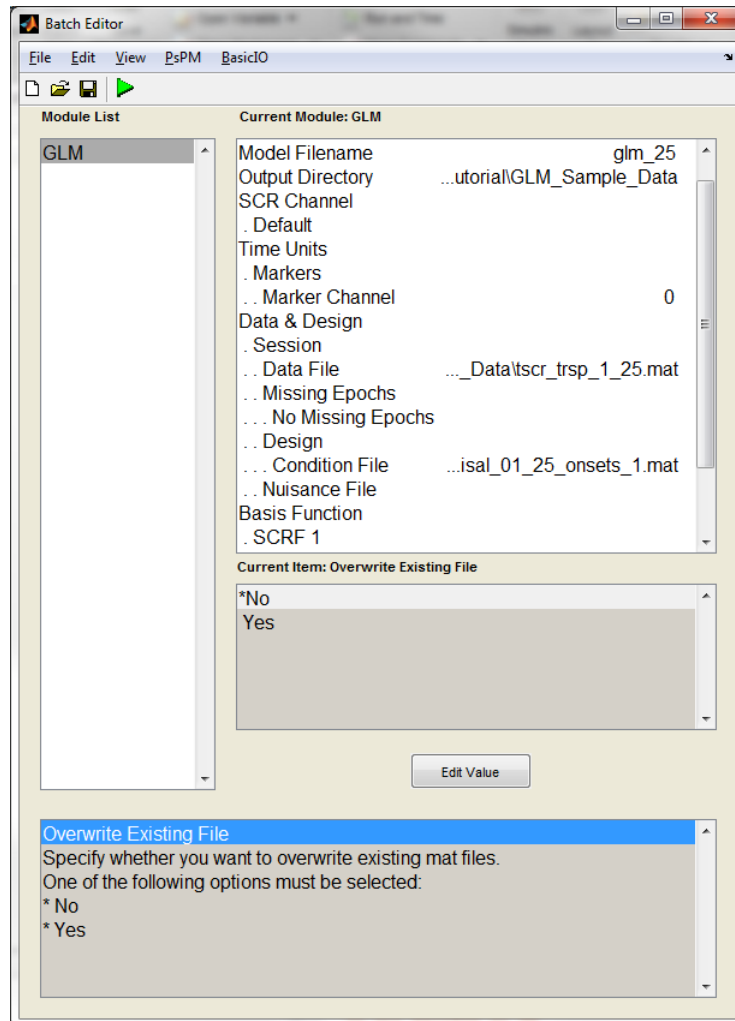


Figure 16.3: Batch editor for First-Level analysis.

- *Basis Function*: We chose the default *SCRF 1*, which is the version with time derivative. The default basis set follows the recommendations by [8].
- *Normalize*: The design of the current data set is “within-subjects.” Therefore, we want to z-normalize the data.
- *Filter Settings*: We choose the default filter settings, which follow the recommendations by [8]:

- first-order low-pass Butterworth filter with a cutoff frequency of 5 Hz
- first-order high-pass Butterworth filter with a cutoff frequency of 0.05 Hz
- Data are resampled to 10 Hz.
- The filter direction is unidirectional.

See Figure 16.3 for a picture of the final batch editor. Again, we recommend saving the batch and script for future use. Run the batch. A mat file with the specified name will be created in the specified folder.

16.4 Review First-Level Model

You can have a look at plots related to the first-level model in the batch editor.

- In the batch editor go to *PsPM* → *First Level* → *Review First-level Model*.
- Specify the Model file that you want to review. Select the mat file containing the GLM (e.g., `glm_25.mat`).
- The *Model Type* is of course GLM in the current example. You can set the following options to get different types of information:
 1. *Design matrix*: On the x-axis, you see the number of regressors in the model. Here we have specified 7 regressors in total. On the y-axis, you see the time course of the experiment. Note that there are 7 regressors because the specification for the *Basis Function* was *SCRf with time derivative*. That is, 3 (conditions times) x 2 (basis functions) + 1 (constant) = 7 regressors. You can see that neutral and aversive are intermixed and fall into three blocks. See Figure 16.4.
 2. *Orthogonality*: On the x- and y-axes you see the specified regressors. Regressor names are additionally specified along the y-axes. The plot depicts the collinearity between regressors. See Figure 16.5.
 3. *Predicted & Observed*: You see the model fit including the observed response over the whole time series, which you can visually compare to the predicted time series by the specified model. Note that the predicted data will never follow the observed data very closely, because we estimated the average response per condition which will deviate from the response in each individual trial. See Figure 16.6.
 4. *Regressor names*: The names of the regressors as specified in the *Conditions File* under *Data & Design* are written to the MATLAB command window. The labels bf 1 and bf 2 refer to the two used basis functions (*SCRf with time derivative*).

5. *Reconstructed*: Here you see the estimated responses per condition for the first basis function. These are estimates of the true responses which contain noise. The noise term can be negative but if all estimated responses across an entire group are negative it is a good idea to look for confounds or correlations in the design. See Figure 16.7.

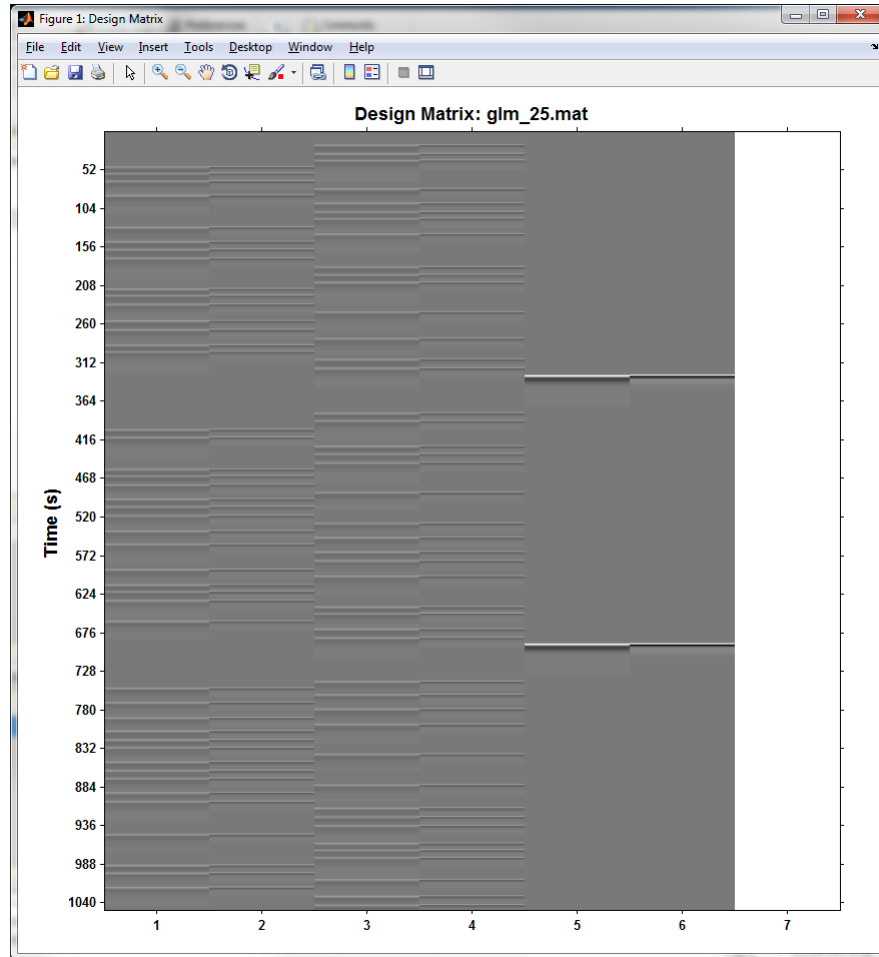


Figure 16.4: Design matrix for sample participant. On the x-axis, you see the number of regressors in the model. There are 7 regressors (i.e., 3 (conditions times) x 2 (basis functions) + 1 (constant)).

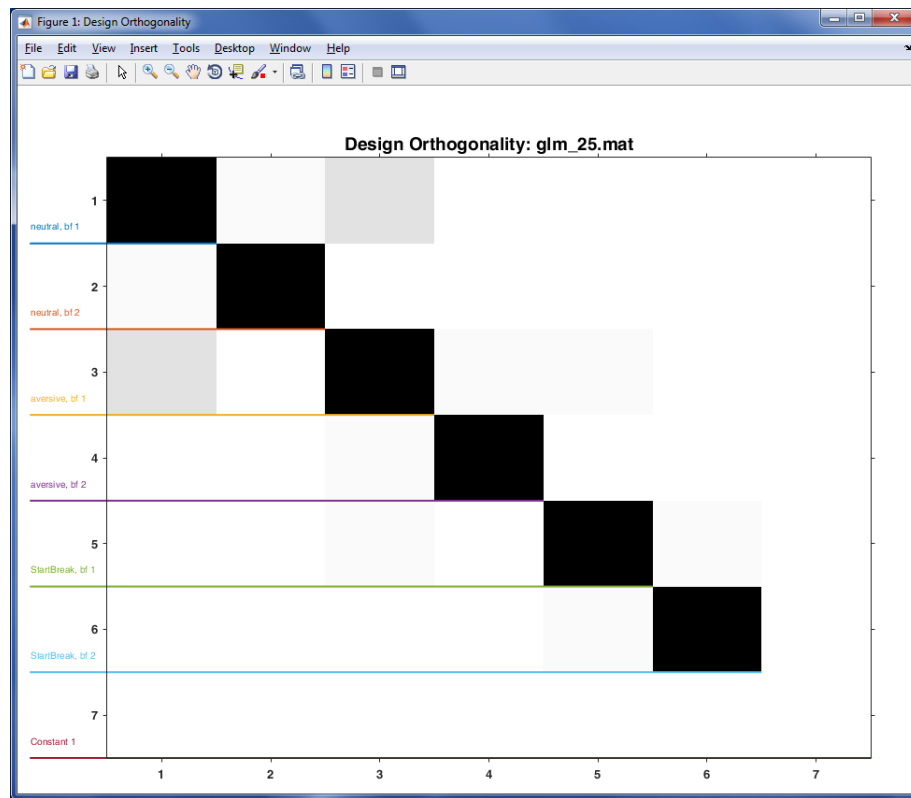


Figure 16.5: Design orthogonality plot for sample participant. On the x- and y-axes you see the 7 specified regressors.

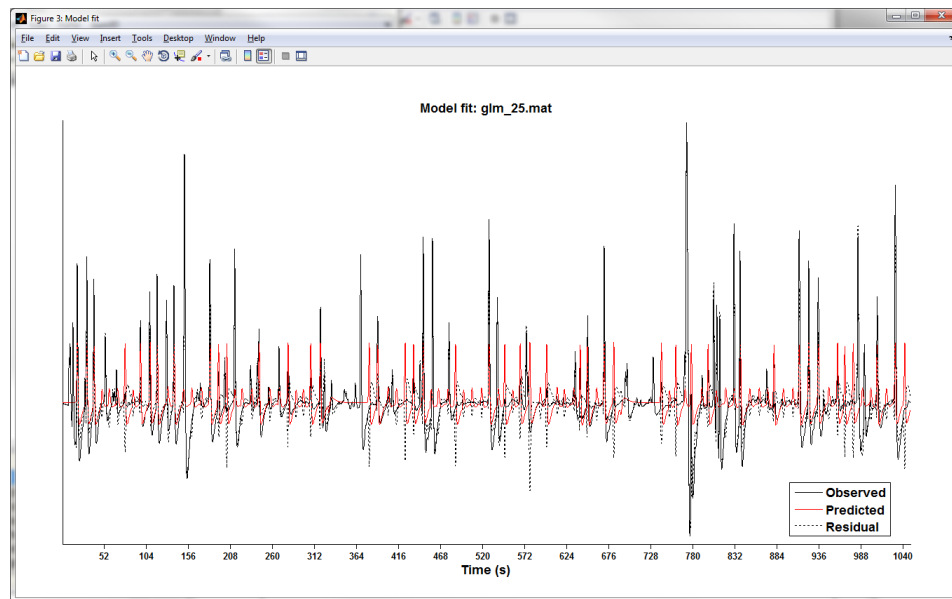


Figure 16.6: Model fit for sample participant. You see the observed response and the predicted response according to the model over the whole time series.

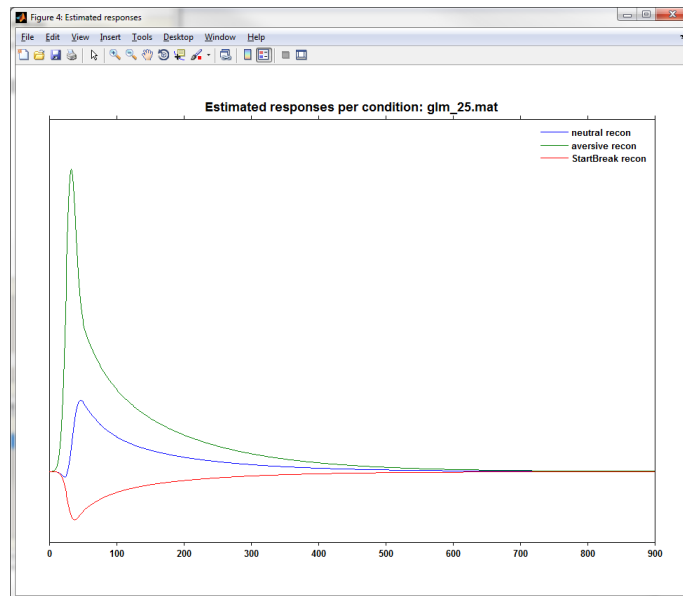


Figure 16.7: Estimated responses per condition for sample participant. You see the estimated responses per condition for the first basis function.

16.5 First-Level Contrast Manager

We want to compare the difference between aversive and neutral pictures across participants (i.e., on the second level). This can be tested in a paired t-test. A paired t-test is a one-sample t-test on difference values between two conditions. The contrast manager allows you to compute such difference values, for each participant (i.e., on the first level).

- In the batch editor go to *PsPM* → *First-Level* → *First-Level Contrasts*.
- *Model File(s)*: Select the mat file containing the GLM (here `glm_25.mat`).
- *Stats type*: You can choose between 3 different options to set up the contrasts. Here, we choose the option *Condition*, which specifies contrasts formulated in terms of conditions and automatically uses only the first basis function (i.e., without derivatives).
- *Contrast*
 - *Contrast Name*: Chose a name so that you can easily refer to the contrast (e.g., `aversive>neutral`)
 - *Contrast Vector*: Specify a vector of the contrast you want to test for. Here, we are interested in the difference between aversive and neutral pictures, i.e., the first and the second condition. Therefore, specify the vector `[-1, 1, 0]`. You could also leave out the last zero because trailing zeros are automatically appended. (But you could not leave out the first zero in a contrast such as `[0 -1 1]`.)

16.6 Export Statistics

You can use this functionality to export all necessary parameters on the screen or into an extra file, which allows you to analyze the data in the statistics program of your choice. For details see *PsPM* → *First Level* → *Export Statistics*.

16.7 Adapting scripts for multiple participants and second-level analyses

For didactic purposes, we have so far only considered one participant. But in most experiments, you want to analyze data from multiple subjects (i.e., a second-level analysis). For a description on how to do this see Chapters 18 and 19. You can find a script that runs the above described analyses for multiple participants at pspm.sourceforge.net (`import_trim_glm_contr_job_loop`).

17 Non-linear SCR tutorial: Delay fear conditioning data

The example data set comprises SCR data from 20 participants, with 40 trials each, which can be downloaded from pspm.sourceforge.net together with the

result files of the model inversion. Participants underwent a differential delay fear conditioning paradigm where coloured circles were presented for 4 seconds each. Either the blue or orange coloured circles (balanced over participants) were probabilistically paired with an electric stimulation (unconditioned stimulus, US) that coterminated with the stimulus (conditioned stimulus, CS+) while the CS- were always presented alone.

Presenting the CS+ causes phasic sympathetic arousal in anticipation of an electric shock. This anticipatory reaction typically occurs with an unknown and variable latency after stimulus onset. For such cases, a GLM should not be used because it assumes that sympathetic arousal follows the stimulus with a fixed latency. In contrast, the non-linear model allows estimating (i) a variable onset within a user-specified time window and (ii) a variable duration of a sympathetic response. Additionally, the non-linear model includes estimation of spontaneous fluctuations that occur between trials.

In this tutorial, the non-linear model is estimated. The estimated parameters can then be used to test the within-subject hypothesis that the sympathetic arousal between CS+ and CS- are different on a group level.

17.1 Setup the Non-Linear Model

In this step you prepare the model estimation. For this, you need to provide timing information about the experimental events which can either be entered manually or as a Matlab file. For large numbers of events as in this experiment, a timing file can easily be created using a few lines of Matlab code. Here we use timing information saved in the trimmed PsPM file. In this file, a trigger was saved at every CS onset. For timing information from other sources, the code has to be adapted accordingly. Go to the Matlab command window and enter the following lines, but replace [insert path!] by the correct path where the filtered SCR data from `pspm.sourceforge.net` is saved on your hard drive, e.g. `C:\PsPM_Tutorial\nonlinear\`.

```
data_path = [insert path!]; % set the correct PsPM file path here!

p = 1; % the first participant
SOA = 3.5; % delay between CS and US onset in seconds

% load events of CS onsets from trimmed scr data
pname = fullfile(data_path, sprintf('tscr_s%i.mat', p));
[sts, infos, data, filestruct] = scr_load_data(pname, 'events');

CS_onset = data{1, 1}.data; % recorded triggers of CS onset in seconds
US_onset = data{1, 1}.data + SOA; % US starts 3.5 seconds after CS

% variable latency for CS response between CS onset and US onset/omission
events{1} = [CS_onset US_onset]; % define an interval of 3.5 seconds for each
trial
% constant onset for US response
```

```

events{2} = US_onset;

save(fullfile(data_path,sprintf('event_timings_s%i.mat',p)), 'events')

```

The resulting file `event_timings_s1.mat` contains the variable `events` with two cells.

- The first cell `events{1}` is a 40 x 2 matrix with the onset and offset of a time window for each trial in which we expect the response to the CS (both CS+ and CS- are treated the same here). We expect the response to the CS to occur with a variable onset in time. Note that the window for the CS response ends when the US starts (or is omitted), i.e. after 3.5 seconds.
- The second cell `events{2}` is a 40 x 1 vector that marks the onset of the electrical stimulation. For this event we expect an evoked response with constant latency after US occurrence. Importantly, we provide timings *both for the occurrence and the omission of the US*. Modelling an unconditioned response in all trials is necessary to get unbiased estimates for the CS responses. In general, the trial structure should always be the same for all trials, across experimental conditions.

Now the non-linear model estimation can be set up (Figure 17.1).

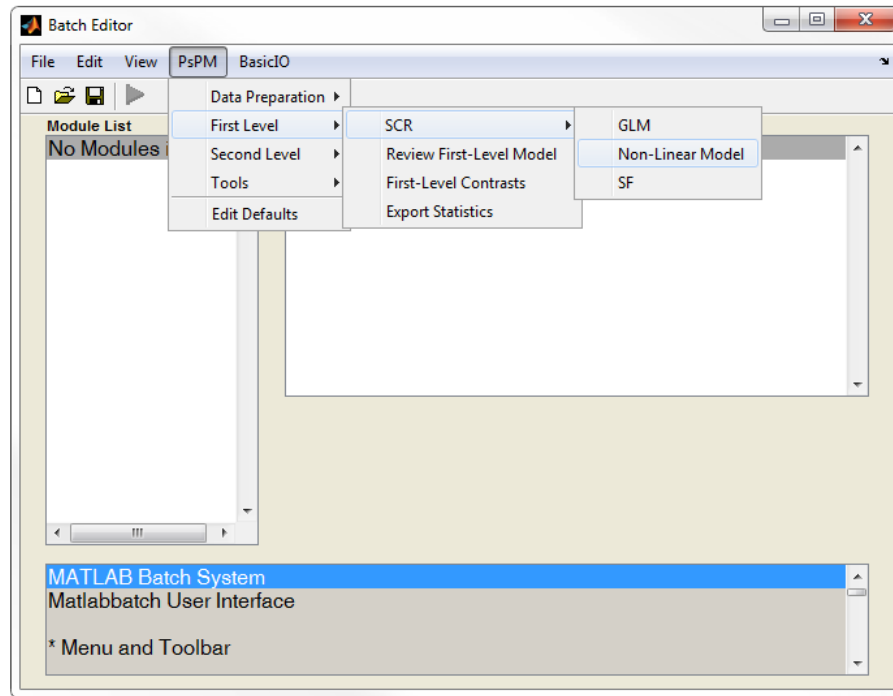


Figure 17.1: Prepare a batch to set up a non linear model for SCR analysis.

- In the batch editor go to *PsPM* → *First Level* → *SCR* → *Non-Linear Model*
- *Model Filename*: dcm_s1
- *Output Directory*: Specify a folder where the model will be saved
- *Channel*: Default
- *Data & Design*: → *New: Session*
 - *Data File*: choose tscr_s1.mat from your hard drive
 - *Design* → *Timing File* → Select the previously created event_timings_s1.mat which was saved to your scr folder
 - *Condition names: New Condition* here we can define conditions that each trial belongs to. Create three new conditions. Note that we split CS+ trials in reinforced (CS+|US+) and non-reinforced (CS+|US-) trials because CS+|US+ trials are excluded from some analyses.
 - * *Condition*
 - *Name*: CS+|US-
 - *Index*: 6 7 11 14 16 18 26 29 38 40

* *Condition*

- *Name:* CS+/US+
- *Index:* 13 17 19 20 21 24 28 31 32 37

* *Condition*

- *Name:* CS-
- *Index:* 1 2 3 4 5 8 9 10 12 15 22 23 25 27 30 33 34 35 36 39

• *Display Options*

- *Display Progress Window:* If you plan to run the estimation in the background, you can turn off the progress window with this option

• *For the remaining fields you can keep the default settings*

Save the batch and script as `batch_model_s1.m` and press run. A window will be displayed that shows the progress of model estimation for each trial. The estimation for an entire session takes several minutes depending on your system. The file `dcm_s1.mat` will be created. If you want to, you can review the first-level model by clicking *Review model* in the PsPM user interface. In the new window (Figure 17.2) add the non-linear model `dcm_s1.mat` and choose *Display All trials for one session*. A graphics window (Fig X) will display the original data (blue) together with the model estimation (green).

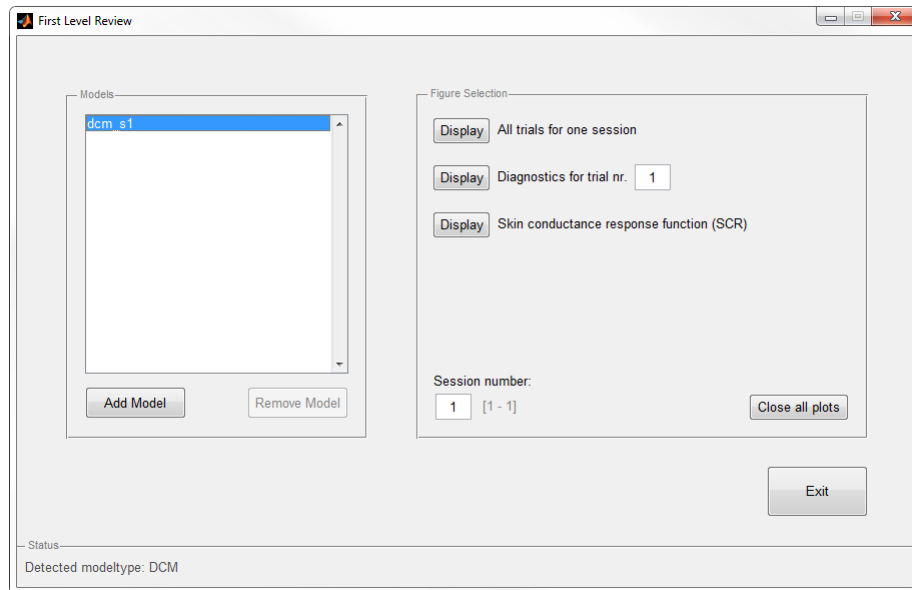


Figure 17.2: Use *Review Model* to inspect parameter estimation for one or multiple trials.

17.2 First-level Contrasts

In this step you specify the hypothesis that a CS+ elicits a stronger sympathetic arousal than a CS- for an individual participant by providing a contrast weight vector.

- In the batch editor go to *PsPM*→*First Level*→*First-level Contrasts*
- *Model File(s)*: Select `dcm_s1.mat`
- *Specify Contrasts on Datatype*: *param*
- *Contrasts: New Contrast*
 - *Contrast*
 - * *Name*: *Fear Learning*
 - * *Contrast Vector*: `-1 -1 -1 -1 -1 2 2 -1 -1 -1 2 -1 0 2 -1 2 0 2 0 0 -1 -1 0 -1 2 -1 0 2 -1 0 0 -1 -1 -1 -1 0 2 -1 2` Note: A weight of +2 is assigned to the CS+|US- because we have twice as many CS- and the contrast vector has to sum up to zero.
 - * *Name*: *Electric Stimulation* We include this contrast optionally to check if the electrical stimulation caused an increase in sympathetic arousal which is a premise for successful fear conditioning.
 - * *Contrast Vector*: `-1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 3 -1 -1 -1 3 -1 3 3 -1 -1 3 -1 -1 -1 3 -1 -1 3 3 -1 -1 -1 -1 3 -1 -1 -1`
- *Delete: existing contrasts*: *No (default)*

Save the batch and script as `batch_contrast_s1.m` and press run. The model file of participant s1 now contains the contrast that can be forwarded to a statistical test on group level. Preparing analyses for more than one scr file is explained in Chapter 18.

17.3 Exporting statistics

PsPM provides basic tools for statistical analysis on the estimates of the non-linear model. Alternatively you can export the results as a text file to use them in different software applications.

- In the batch editor go to *SCR*→*First Level*→*Export Data*
- *Model File(s)*: Select `dcm_s1.mat`
- *Specify Export on Datatype*: *param*
- *Target*
 - *Filename* Enter `dcm_s01`
- *Specify Delimiter for Output File*

– *Semicolon*

The text file will be saved to Matlab’s current working directory.

18 Adapting scripts for multiple participants

In most experiments, you want to analyze data from multiple subjects, which implies that you have to repeat model estimation several times. There are two simple strategies to make this easier.

- Use dependencies: You can specify all steps for one subject in one go. At some points, you need to specify a file from a previous step (e.g., when trimming you need the file containing the imported data). In these cases, you can use the button “Dependency” to specify the corresponding file.
- Loop over participants in the script: You can easily adapt the scripts for many subjects by including a loop and adapting the file names. This is independent of whether or not you use dependencies. To show you how this works, see the examples below.

18.1 Importing and trimming data

Here, we create an example script for importing and trimming data. We chose these steps since they are required in all types of analysis. The current example is based on the Appraisal dataset described in Chapter 16.

- In the batch editor specify all parameters in PsPM → Data Preparation → Import.
- You do not need to specify the SCR Data File. This will later be put in the script that loops over subjects.
- In the batch editor specify all parameters in PsPM → Data Preparation → Trim.
- Use the dependency button to select the imported Data File.
- Save batch and script.
- Open the saved job script (e.g., `batch_import_trim_job.m`) and build a loop around the lines of code that were saved. In this loop, create a subject-specific filename (and make sure to include the whole path to the files in the variable `data_path`).

```
data_path = [insert path!];

for p = 25:39; % participants
    % load participant-specific raw data
    spike.datafile = {fullfile(data_path,sprintf('trsp_1_%i.smr',p))};
```



```

spike.importtype{1}.scr.chan_nr.chan_nr_spec = 2;
spike.importtype{1}.scr.transfer.none = true;
spike.importtype{2}.marker.chan_nr.chan_nr_spec = 0;
matlabbatch{1}.pspm{1}.prep{1}.import.datatype.spike = spike;
matlabbatch{1}.pspm{1}.prep{1}.import.overwrite = false;
matlabbatch{2}.pspm{1}.prep{1}.trim.datafile(1) = ...
    cfg_dep('Import: Output File', substruct('.', ...
        'val', '{1}', '{1}', '.', 'val', ...
        '{1}', '{1}', '.', 'val', '{1}', '{1}', substruct('()', {' ':''}));
matlabbatch{2}.pspm{1}.prep{1}.trim.ref.ref_mrk.from = 110;
matlabbatch{2}.pspm{1}.prep{1}.trim.ref.ref_mrk.to = 10;
matlabbatch{2}.pspm{1}.prep{1}.trim.ref.ref_mrk.mrk_chan.chan_def = 0;
matlabbatch{2}.pspm{1}.prep{1}.trim.overwrite = false;

% run batch
scr_jobman('initcfg');
scr_jobman('run', matlabbatch);

end

```

Run the script. The folder `data_path` now contains trimmed scr files for all subjects.

18.2 Inverting non-linear models

Here we adapt the model inversion from Chapter 17 to multiple subjects. We use similar loops as above to create timing files and PsPM batches.

First, open the MATLAB script that created the timing file `event_timings_s1.mat` and construct a loop around it for subjects 2 to 20. Execute the script to obtain files containing timing information for subjects 2 to 20. Alternatively you can use the timing files for subjects 2 to 20 downloaded from pspm.sourceforge.net.

Next, open the saved job script (e.g., `batch_model_s1_job.m`) created in Chapter 17 and build a loop around the lines of code that were saved. Make sure to include the whole path to the files in the variable `data_path`. You can use the following code as guideline.

```

% set the path where you saved the scr data files
data_path = [insert_path!];

% set the path where you saved the model file of participant 1
model_path = [insert_path!]; % initiate PsPM scr_init % loop through participants
2 to 20

% initialize PsPM
scr_init
scr_jobman('initcfg')

```

```

for p = 2:20

    clear matlabbatch dcm
    dcm.modelfile = ['dcm_s' num2str(p)];
    dcm.outdir = {model_path};
    dcm.chan.chan_def = 0;
    dcm.session.datafile = ...
        {fullfile(data_path,['tscr_s' num2str(p) '.mat'])};
    dcm.session.timing.timingfile = ...
        {fullfile(data_path,['event_timings_s' num2str(p) '.mat'])};
    dcm.session.condition(1).name = 'CS+|US-';
    dcm.session.condition(1).index = [6 7 11 14 16 18 26 29 38 40];
    dcm.session.condition(2).name = 'CS+|US+';
    dcm.session.condition(2).index = [13 17 19 20 21 24 28 31 32 37];
    dcm.session.condition(3).name = 'CS-';
    dcm.session.condition(3).index = ...
        [1 2 3 4 5 8 9 10 12 15 22 23 25 27 30 33 34 35 36 39];
    dcm.data_options.norm = 0;
    dcm.data_options.filter.def = 0;
    dcm.resp_options.crfupdate = 0;
    dcm.resp_options.indrf = 0;
    dcm.resp_options.getrf = 0;
    dcm.resp_options.rf = 0;
    dcm.inv_options.depth = 2;
    dcm.inv_options.sfpres = 2;
    dcm.inv_options.sfpres = 5;
    dcm.inv_options.sffreq = 0.5;
    dcm.inv_options.sclpres = 2;
    dcm.inv_options.sclpost = 5;
    dcm.inv_options.ascr_sigma_offset = 0.1;
    dcm.disp_options.dispwin = 0;
    dcm.disp_options.dispsmallwin = 0;

    matlabbatch{1}.pspm{1}.first_level{1}.scr{1}.dcm = dcm;

    % run batch
    scr_jobman('run', matlabbatch);

end

```

Similarly to the previous step, the batch of the first-level Contrast of participant 1 is adapted to participants 2 to 20. Run the following code in MATLAB, but replace [insert path!] with the path on your hard drive where you saved dcm_s1.mat:

```

% set the path where you saved the estimated non-linear model
model_path = [insert path!];

% initialize PsPM

```

```

scr_init
scr_jobman('initcfg')

% loop through participants 2 to 20
for p = 2:20

    clear matlabbatch
    matlabbatch{1}.pspm{1}.first_level{1}.contrast.modelfile = ...
        {fullfile(model_path,['dcm_s' num2str(p) '.mat'])};
    matlabbatch{1}.pspm{1}.first_level{1}.contrast.datatype = 'param';
    matlabbatch{1}.pspm{1}.first_level{1}.contrast.con(1).conname = 'Fear Learning';
    matlabbatch{1}.pspm{1}.first_level{1}.contrast.con(1).convec = ...
        [-1 -1 -1 -1 -1 2 2 -1 -1 -1 2 -1 0 2 -1 2 0 2 ...
         0 0 0 -1 -1 0 -1 2 -1 0 2 -1 0 0 -1 -1 -1 -1 0 2 -1 2];
    matlabbatch{1}.pspm{1}.first_level{1}.contrast.con(2).conname = ...
        'Electric Stimulation';
    matlabbatch{1}.pspm{1}.first_level{1}.contrast.con(2).convec = ...
        [-1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 3 -1 -1 -1 ...
         3 -1 3 3 3 -1 -1 3 -1 -1 -1 3 -1 -1 3 3 -1 -1 -1 -1 3 -1 -1 -1];
    matlabbatch{1}.pspm{1}.first_level{1}.contrast.deletecon = true;

    % run batch manually
    scr_jobman('run', matlabbatch);

end

```

Run the script. The statistics for each contrast are now added to the model file.

19 Second-level Contrast Manager

In most cases, we want to compare the difference between conditions across participants on a group level (i.e., the second level in a hierarchical model). Each participant represents one data point that goes into a one sample t-test.

Below we demonstrate how to set-up Second-level contrasts for GLM and non-linear models.

19.1 GLM

For the appraisal data of Chapter 16.

19.1.1 Define Second-Level Model

- In the batch editor go to *PsPM*→*Second Level*→*Define Second-Level Model*.
 - *Test Type: One Sample T-Test*
 - *Model File(s)*: Select the model files from all participants
 - *Output Directory*: Choose a location to save the group result

- *Filename for Output Model*: Chose a name so that you can easily refer to the contrast
- *Define Contrast: Read from First Model File*: Choose *All Contrasts*. This will select the contrast(s) that we created in the first level (i.e., in our case *aversive>neutral*)

19.1.2 Report Second-Level Results

- In the batch editor go to *PsPM* → *Second Level* → *Report Second-Level Results*.
 - *Model File*: Select the second level model file that you created in the previous step.
 - *Contrast Vector*: Leave empty because we want all contrasts to be reported.

Run the batch. A figure appears that shows you a bar graph of the mean of the parameter estimates and the statistics will be printed to the MATLAB command window.

19.2 Non-linear models

Here, we test the difference in anticipatory sympathetic arousal elicited by a CS+ vs CS- on a group level (see Chapter 17). As a supplementary hypothesis we want to check if the US+ indeed elicited a stronger response than the US-. From the 1st level contrast, eight statistics were generated for each model file. Use the *Review Model* utility from the PsPM main GUI to get a list of all contrasts. In the *First Level Review Manager*, click on *Add Model*, choose any model file created previously and press *Done*. Now press the Show button next to *Contrast names in command window* (Figure 19.1) to get a list of all contrasts:

- *Contrast 1: Fear Learning - Flexible response # 1: amplitude*
- *Contrast 2: Electric Stimulation - Flexible response # 1: amplitude*
- *Contrast 3: Fear Learning - Flexible response # 1: peak latency*
- *Contrast 4: Electric Stimulation - Flexible response # 1: peak latency*
- *Contrast 5: Fear Learning - Flexible response # 1: dispersion*
- *Contrast 6: Electric Stimulation - Flexible response # 1: dispersion*
- *Contrast 7: Fear Learning - Fixed response # 1 response amplitude*
- *Contrast 8: Electric Stimulation - Fixed response # 1 response amplitude*

Our hypothesis is concerned only with the response amplitude of the flexible event (anticipation of the CS) and the response amplitude of the fixed event (electrical stimulation), which are the first and eighth contrasts. The indices of these two contrasts are used for the setup of the Second-Level model below.

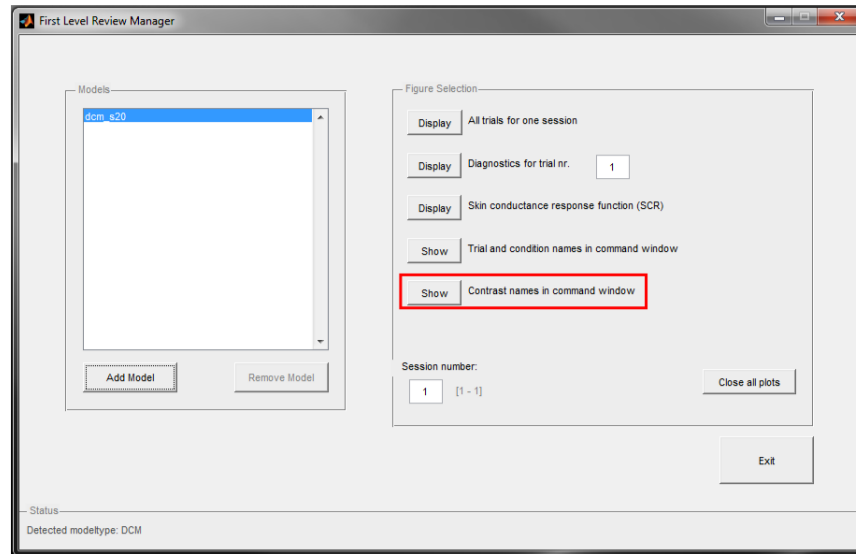


Figure 19.1: The First Level Review Manager displays all contrasts that are stored in a model file.

- In the batch editor go to PsPM→Second Level→Define Second-Level Model
- Test Type: One Sample T-Test
- Model File(s): Select the model files from all participants
- Output Directory: Choose a location to save the group result
- Filename for Output Model: Fear_Learning
- Define Contrast: Read from First Model File
 - Contrast Vector: [1, 8]
- Overwrite Existing File: No (default)

Run the batch. You can display the results of the second level contrasts by pressing *Report 2nd level result* in the PsPM user interface and choosing **Fear_Learning.mat**. A Figure displays the mean differences and standard error for the hypothesis that the CS+ elicits a stronger sympathetic arousal than CS- and that an electric stimulation results in an increase in sympathetic arousal (Figure 19.2).

Statistical parameters are printed in the MATLAB command window (Figure 19.3).

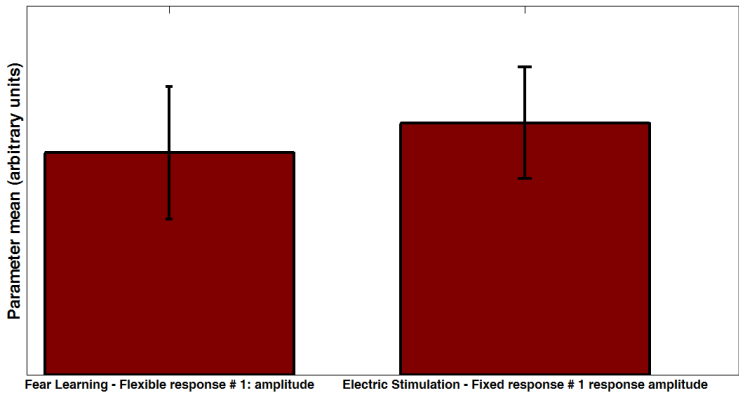


Figure 19.2: Display of results from a group analysis (2nd level). Left bar: difference in amplitude of sympathetic arousal (aSA) to CS+|US- minus CS-. Right bar: difference in aSA to US+ minus US-

Statistics:					
mean	sem	t	p	df	Contrast name
5.16	1.54	3.34	0.0035	19	Fear Learning - Flexible response # 1: amplitude
5.85	1.30	4.52	0.0002	19	Electric Stimulation - Fixed response # 1 response amplitude

SCRalyze (c) Dominik R. Bach, Wellcome Trust Centre for Neuroimaging, UCL London UK

Figure 19.3: Statistics from one-sampled t-tests CS|US- minus CS- and US+ minus US- for 20 participants.

Part IV

How to reference PsPM

To justify our continued effort in the face of tight resources, we ask you acknowledge PsPM when you use it: Data were analysed using PsPM [version number], available at pspm.sourceforge.net

We suggest you reference our papers to justify your analysis steps and models in the following way:

- General PsPM reference: Bach DR, & Friston KJ (2013). Model-based analysis of skin conductance responses: Towards causal models in psychophysiology. *Psychophysiology*, 50, 15-22.
- GLM for SCR

- general reference: Bach DR, Flandin G, Friston KJ, & Dolan RJ (2009). Time-series analysis for rapid event-related skin conductance responses. *Journal of Neuroscience Methods*, 184, 224-234.
- canonical SCRF: Bach DR, Flandin G, Friston KJ, & Dolan RJ (2010). Modelling event-related skin conductance responses. *International Journal of Psychophysiology*, 75, 349-356.
- optimised filter settings: Bach DR, Friston KJ, Dolan RJ (2013). An improved algorithm for model-based analysis of evoked skin conductance responses. *Biological Psychology*, 94, 490-497.
- comparison with Ledalab and peak-scoring methods: Bach DR (2014). A head-to-head comparison of SCRalyze and Ledalab, two model-based methods for skin conductance analysis. *Biological Psychology*, 103, 63-88.
- non-linear model for event-related SCR:
 - general reference: Bach DR, Daunizeau J, Friston KJ, & Dolan RJ (2010). Dynamic causal modelling of anticipatory skin conductance responses. *Biological Psychology*, 85, 163-70.
 - optimised filter settings: Staib M, Castegnetti G, Bach DR (2015). Optimising a model-based approach to inferring fear learning from skin conductance responses. *Journal of Neuroscience Methods*, 255, 131-138.
- non-linear model for SF:
 - general reference: Bach DR, Daunizeau J, Kuelzow N, Friston KJ, & Dolan RJ (2011). Dynamic causal modelling of spontaneous fluctuations in skin conductance. *Psychophysiology*, 48, 252-57.
 - canonical SCRF: Bach DR, Friston KJ, & Dolan RJ (2010). Analytic measures for quantification of arousal from spontaneous skin conductance fluctuations. *International Journal of Psychophysiology*, 76, 52-55.
 - MP algorithm: Bach DR, Staib M (2015). A matching pursuit algorithm for inferring tonic sympathetic arousal from spontaneous skin conductance fluctuations. *Psychophysiology*, 52, 1106-12.
- GLM for evoked HPR: Paulus PC, Castegnetti G, & Bach DR (2016). Modeling event-related heart period responses. *Psychophysiology*, 53, 837-846.
- GLM for fear-conditioned HPR: Castegnetti G, Tzovara A, Staib M, Paulus PC, Hofer N, & Bach DR (2016). Modeling fear-conditioned bradycardia in humans. *Psychophysiology*, 53, 930-939.

- GLM for evoked respiratory responses: Bach DR, Gerster S, Tzovara A, Castegnetti G (2016). A linear model for event-related respiration responses. *Journal of Neuroscience Methods*, 270, 174-155.
- GLM for fear-conditioned RAR: Castegnetti C, Tzovara A, Staib M, Gerster S, Bach DR (2016). Assessing fear memory via conditioned respiratory amplitude responses. submitted.
- GLM for illuminance-elicited PSR: Korn CW & Bach DR (2016). A solid frame for the window on cognition: Modeling event-related pupil responses. *Journal of Vision*, 16, 28.
- GLM for fear-conditioned PSR: Korn CW, Staib M, Tzovara A, Castegnetti G, Bach DR (2016). A pupil size response model to quantify fear conditioning. submitted.

Part V

Release notes

20 PsPM Version 3.0

Import

New data types were implemented

- Noldus Observer compatible
- Eyelink

Untested data types

CNT data import has not been not tested – please contact the developers with sample data files.

Filtering for SCR models

Previous versions of PsPM have used a bi-directional high pass filter of 0.0159 for all SCR analyses. We have recently shown a better predictive validity for GLM with a unidirectional filter of 0.05 Hz [8]. This also implies that different filters are used for different models. These are now set as defaults, and the way the default settings are implemented has changed. It is now possible to alter the filter settings in the model definition, although we discourage this.

New SF method

A matching pursuit algorithm is now implemented to approximate the number of spontaneous fluctuations (SF) in skin conductance [25].

General linear modelling (GLM)

Parametric modulators

Parametric modulators (pmods) are z-normalised before being entered into the design matrix. This is to account for possibly very large or very small numbers – a badly scaled design matrix can cause induced instability in the inversion. The parameter estimates of the pmods were not transformed back in previous versions, i. e. the parameter estimates of the pmods were independent of the scaling of the pmods. This is appropriate as long as they are the same for all datasets, or if analysis is done strictly on a within-subject level. Some researchers have reported designs in which inference was to be drawn on parameter estimates of pmods on a between-group level, and where the pmods systematically differed between these groups. To account for this possibility, the parameter estimates are now transformed back, such that they refer to the pmods in their original scaling/units.

Parametric confounds

Previous versions of PsPM contained an option to include a parametric modulator across all event types, to account for confounds across all conditions. For example, in an experiment with 5 conditions, one could have included 5 regressors, plus one reaction time confound across all events, without including an associated regressor that contains the event onsets for all these events. This option was removed.

Design matrix filtering

Previous versions of PsPM filtered the design matrix after orthogonalisation of basis sets. This can introduce unwanted dependencies between regressors. PsPM 3.0 filters the regressors first, then orthogonalises the basis sets.

File format

Some minor changes have been made to the data format. In particular, marker channels from previous versions can not be read with the current version - such data files have to be re-imported. Model files have changed drastically, and model files from previous versions can not be read with the current version of the software.

VB inversion

The VBA toolbox (<http://code.google.com/p/mbb-vb-toolbox/>) was updated in October 2014 [23]. This update incorporates bugfixes in this toolbox and slightly changed the model estimates in our test models. In terms of predictive validity, we noted that there was no consistent benefit of the old or new version of this code (Figure 20.1).

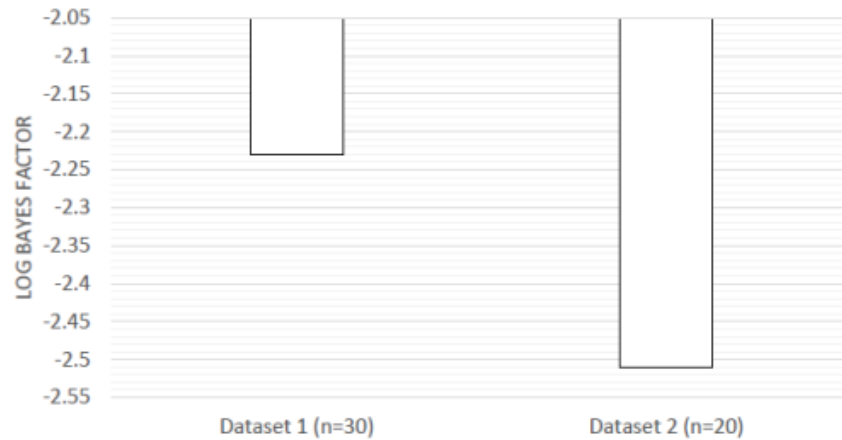


Figure 20.1: Model comparison between old and new versions of the VBA toolbox, based on two delay fear conditioning datasets. The log Bayes factor quantifies the difference between negative log likelihood (nLL) of parameter estimates obtained from model inversion using the old and new version of VBA. A difference in nLL above 3 indicates significant differences in model evidence which is not exceeded for either data set. Analysis and figure contributed by Matthias Staib.

21 PsPM Version 3.0.1

Import

New data types were implemented

- DATAQ Windaq (no ActiveX needed)
- European Data Format (EDF)

Tools

'Preprocess respiration traces' replaces 'Convert Respiration to Respiration Period'. It supports conversions into the following datatypes:

- Respiration prerioid (old funtionality)
- Respiration amplitude
- Respiration line length
- Respiration time stamp

First level contrast

Z-score parameter estimates

The function `scr_con1` now supports z-scoring trial-by-trial parameter estimates. If selected, all parameter estimates for the same event type, across all trials, will be z-scored before computing the contrast. This option is currently only available for non-linear models.

Review first level model

Next to the regressors on the x- and y-axes, orthogonality plots newly display regressor names along the y-axes.

22 PsPM Version 3.0.2

GLM

Problem with multiple sessions in Design matrix fixed.

23 PsPM Version 3.1

General linear modelling (GLM)

New modalities

For the first time in PsPM, we introduce models for data types other than SCR:

- GLM for evoked HPR
- GLM for fear-conditioned HPR
- GLM for evoked RA
- GLM for fear-conditioned RA
- GLM for evoked RFR
- GLM for evoked RP
- GLM for fear-conditioned PS

Tools & Data preprocessing

Tools are split up into Tools & Data preprocessing. The content of each section is listed below. New functions are written in [green](#).

Tools

- Display data
- Rename file
- Split sessions
- Artefact removal
- Downsample data
- Interpolate missing data
- Extract segments
- Segment mean

Data preprocessing

- Preprocess heart data
- Preprocess respiration data
- Prepare illuminance GLM
- Find valid fixations
- Convert pupil data
- Find startle sound onsets

Data preparation

Import

Support for Philips Scanphyslog files and for bioread-converted AcqKnowledge files has been added to the import function.

Part VI

Acknowledgements

SCRalyze versions 1-2 were developed at the FIL, Wellcome Trust Centre for Neuroimaging, University College London, under the auspices of Karl J. Friston and Raymond J. Dolan. Guillaume Flandin contributed to GLM, and Jean Daunizeau to DCM. Eric Featherstone, Alfonso Reid, Oliver Josephs, and Chloe Hutton helped with the import functions. This development was funded by the Swiss National Science Foundation with a personal grant to Dominik R. Bach, and by the Wellcome Trust with a programme grant to Raymond J. Dolan.

SCRalyze included a number of SPM functions. For import of spike data, PsPM makes use of the SON library written by Malcolm Lidieth at King's College London, and of functions provided by the SPM physiology toolbox, written by Chloe Hutton and Eric Featherstone at the FIL. Biopac AcqKnowledge import uses a routine created by Sebastien Authier and Vincent Finnerty at the University of Montreal. The DCM inversion uses a variational Bayesian inversion scheme written by Jean Daunizeau.

PsPM 3.0 was developed at the University of Zurich, funded by the University of Zurich and by the Swiss National Science Foundation with a project grant. The Matlabbatch GUI was written by Gabriel Gräni at University of Zurich. Help texts and tutorial were developed by Christoph Korn and Matthias Staib. The data display was written by Philipp C Paulus, University of Dresden. The test environment was contributed by Linus Rüttimann, and extended by Tobias Moser, both University of Zurich.

Various models have been developed by different researchers. These are:

- Dominik R. Bach: SCR models and GLM for evoked respiratory responses
- Matthias Staib: Optimisation of non-linear SCR model
- Philipp Paulus: GLM for evoked HPR
- Giuseppe Castegnetti: GLM for fear-conditioned HPR and RAR
- Christoph Korn: PSM models

Part VII

References

References

- [1] Bach, D. R. & Friston, K. J. (2013) Model-based analysis of skin conductance responses: Towards causal models in psychophysiology. *Psychophysiology* **50**, 15–22.
- [2] Burnham, K. P. & Anderson, D. R. (2004) Multimodel inference understanding aic and bic in model selection. *Sociological methods & research* **33**, 261–304.
- [3] Penny, W. D., Stephan, K. E., Mechelli, A., & Friston, K. J. (2004) Comparing dynamic causal models. *Neuroimage* **22**, 1157–72.
- [4] Alexander, D. M., Trengove, C., Johnston, P., Cooper, T., August, J. P., & Gordon, E. (2005) Separating individual skin conductance responses in a short interstimulus-interval paradigm. *J Neurosci Methods* **146**, 116–23.

- [5] Bach, D. R, Flandin, G, Friston, K. J, & Dolan, R. J. (2009) Time-series analysis for rapid event-related skin conductance responses. *J Neurosci Methods* **184**, 224–34.
- [6] Benedek, M & Kaernbach, C. (2010) Decomposition of skin conductance data by means of nonnegative deconvolution. *Psychophysiology* **47**, 647–58.
- [7] Benedek, M & Kaernbach, C. (2010) A continuous measure of phasic electrodermal activity. *J Neurosci Methods* **190**, 80–91.
- [8] Bach, D. R, Friston, K. J, & Dolan, R. J. (2013) An improved algorithm for model-based analysis of evoked skin conductance responses. *Biol Psychol* **94**, 490–7.
- [9] Bach, D. R. (2014) A head-to-head comparison of scralyze and ledalab, two model-based methods for skin conductance analysis. *Biol Psychol* **103**, 63–8.
- [10] Staib, M, Castegnetti, G, & Bach, D. R. (2015) Optimising a model-based approach to inferring fear learning from skin conductance responses. *J Neurosci Methods* **255**, 131–8.
- [11] Daunizeau, J, Friston, K. J, & Kiebel, S. J. (2009) Variational bayesian identification and prediction of stochastic nonlinear dynamic causal models. *Physica D* **238**, 2089–2118.
- [12] Boucsein, W. (2012) *Electrodermal activity*. (Springer Science & Business Media).
- [13] Bini, G, Hagbarth, K. E, Hynninen, P, & Wallin, B. G. (1980) Thermoregulatory and rhythm-generating mechanisms governing the sudomotor and vasoconstrictor outflow in human cutaneous nerves. *J Physiol* **306**, 537–52.
- [14] Sugeno, J, Iwase, S, Mano, T, & Ogawa, T. (1990) Identification of sudomotor activity in cutaneous sympathetic nerves using sweat expulsion as the effector response. *Eur J Appl Physiol Occup Physiol* **61**, 302–8.
- [15] Kunimoto, M, Kirnö, K, Elam, M, & Wallin, B. G. (1991) Neuroeffector characteristics of sweat glands in the human hand activated by regular neural stimuli. *J Physiol* **442**, 391–411.
- [16] Kunimoto, M, Kirnö, K, Elam, M, Karlsson, T, & Wallin, B. G. (1992) Neuro-effector characteristics of sweat glands in the human hand activated by irregular stimuli. *Acta Physiol Scand* **146**, 261–9.
- [17] Bach, D. R, Flandin, G, Friston, K. J, & Dolan, R. J. (2010) Modelling event-related skin conductance responses. *Int J Psychophysiol* **75**, 349–56.
- [18] Kunimoto, M, Kirnö, K, Elam, M, Karlsson, T, & Wallin, B. G. (1992) Non-linearity of skin resistance response to intraneural electrical stimulation of sudomotor nerves. *Acta Physiol Scand* **146**, 385–92.

- [19] Friston, K. J, Josepshs, O, Rees, G, & Turner, R. (1998) Nonlinear event-related responses in fmri. *Magn Reson Med* **39**, 41–52.
- [20] Friston, K. J, Mechelli, A, Turner, R, & Price, C. J. (2000) Nonlinear responses in fmri: the balloon model, volterra kernels, and other hemodynamics. *Neuroimage* **12**, 466–77.
- [21] Bach, D. R, Friston, K. J, & Dolan, R. J. (2010) Analytic measures for quantification of arousal from spontaneous skin conductance fluctuations. *Int J Psychophysiol* **76**, 52–5.
- [22] Bach, D. R, Daunizeau, J, Friston, K. J, & Dolan, R. J. (2010) Dynamic causal modelling of anticipatory skin conductance responses. *Biol Psychol* **85**, 163–70.
- [23] Daunizeau, J, Adam, V, & Rigoux, L. (2014) Vba: a probabilistic treatment of nonlinear models for neurobiological and behavioural data. *PLoS Comput Biol* **10**, e1003441.
- [24] Bach, D. R, Daunizeau, J, Kuelzow, N, Friston, K. J, & Dolan, R. J. (2011) Dynamic causal modeling of spontaneous fluctuations in skin conductance. *Psychophysiology* **48**, 252–257.
- [25] Bach, D. R & Staib, M. (2015) A matching pursuit algorithm for inferring tonic sympathetic arousal from spontaneous skin conductance fluctuations. *Psychophysiology*.
- [26] Lim, C. L, Rennie, C, Barry, R. J, Bahramali, H, Lazzaro, I, Manor, B, & Gordon, E. (1997) Decomposing skin conductance into tonic and phasic components. *Int J Psychophysiol* **25**, 97–109.
- [27] Greco, A, Lanata, A, Valenza, G, Scilingo, E. P, & Citi, L. (2014) *Electrodermal activity processing: A convex optimization approach*. (IEEE), pp. 2290–2293.
- [28] Berntson, G. G, Cacioppo, J. T, & Quigley, K. S. (1995) The metrics of cardiac chronotropism: Biometric perspectives. *Psychophysiology* **32**, 162–171.
- [29] Paulus, P. C, Castegnetti, G, & Bach, D. R. (2016) Modeling event-related heart period responses. *Psychophysiology* **53**, 837–846.
- [30] Castegnetti, G, Tzovara, A, Staib, M, Paulus, P. C, Hofer, N, & Bach, D. R. (2016) Modeling fear-conditioned bradycardia in humans. *Psychophysiology* **53**, 930–939.
- [31] Bradley, M. M, Codispoti, M, Cuthbert, B. N, & Lang, P. J. (2001) Emotion and motivation i: Defensive and appetitive reactions in picture processing. *Emotion* **1**, 276–298.

- [32] Castegnetti, G, Tzovara, A, Staib, M, Gerster, S, & Bach, D. R. (2016) Assessing fear learning via conditioned respiratory amplitude responses. in press.
- [33] Pan, J & Tompkins, W. J. (1985) A real-time qrs detection algorithm. *IEEE Trans Biomed Eng* **32**, 230–6.
- [34] McDougal, D & Gamlin, P. (2008) Pupillary control pathways. *The senses: A comprehensive reference* **1**, 521–536.
- [35] Korn, C. W & Bach, D. R. (2016) A solid frame for the window on cognition: Modeling event-related pupil responses. *Journal of Vision* **16**, 28.
- [36] Watson, A. B & Yellott, J. I. (2012) A unified formula for light-adapted pupil size. *Journal of Vision* **12**, 12–12.
- [37] Cacioppo, J. T, Tassinary, L. G, & Berntson, G. (2007) *Handbook of psychophysiology*. (Cambridge University Press).
- [38] Wientjes, C. J & Grossman, P. (1998) Respiratory psychophysiology as a discipline: introduction to the special issue. *Biol. Psychol* **49**, 1–8.
- [39] Binks, A. P, Banzett, R. B, & Duvivier, C. (2006) An inexpensive, mri compatible device to measure tidal volume from chest-wall circumference. *Physiological measurement* **28**, 149.
- [40] Bach, D. R, Gerster, S, Tzovara, A, & Castegnetti, G. (2016) A linear model for event-related respiration responses. *J Neurosci Methods* **270**, 147–155.
- [41] Hayes, T. R & Petrov, A. A. (2015) Mapping and correcting the influence of gaze position on pupil size measurements. *Behavior Research Methods* **48**, 510–527.