bistablehistory: an R package for history-dependent analysis of perceptual time series

Alexander Pastukhov[1, 2]

1 Department of General Psychology and Methodology, University of Bamberg, Bamberg, Bavaria, Germany. **2** Forschungsgruppe EPÆG (Ergonomics, Psychological Æsthetics, Gestalt), Bamberg, Bavaria, Germany.

Summary

Our perception is subject to a process of adaptation that changes its operating properties (Clifford et al., 2007). This process manifests itself in a plethora of perceptual illusions and so-called aftereffects. It also plays an important role during the perception of multistable stimuli, such as a Necker cube (Fig. 1A). These are compatible with several, typically two, comparably likely perceptual interpretations. In the case of the Necker cube, one can perceive it as "upwards" or "downwards," and during continuous viewing the perception switches between these alternatives (Fig. 1B).
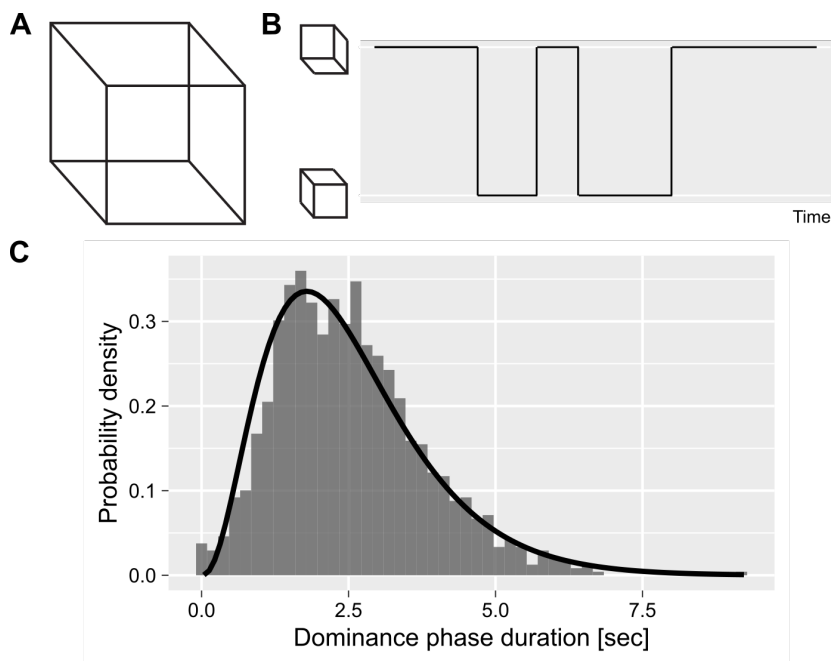
Figure 1: Figure 1. Perception of Necker cube stimulus. A) Necker cube. B) Schematic time series of perceptual alternations. C) Example distribution of perceptual dominance phases' duration fitting with the Gamma distribution.

Typically, time series for such multistable stimuli are fitted using the Gamma distribution (Fig. 1C). This assumes that individual dominance phase durations are exchangeable, i.e., the order in which they are drawn is unimportant. However, this ignores the effect of prior perception through adaptation (Ee, 2009) that makes individual dominance phases serially dependent on

prior ones, violating assumptions about independent and identically distributed samples. In other words, each dominance phase is drawn from its specific distribution, whose parameters are also determined by the prior perceptual history. The `bistablehistory` package solves this problem by accounting for the slow accumulation process via a homogeneous first-order process (Pastukhov & Braun, 2011), providing tools for fitting time series using various distributions. It also allows for fitting while accounting for additional random or fixed factors. In addition, it provides a tool for extracting the estimated accumulated adaptation or computing it directly for further usage. The package aims to streamline the time series analysis for perceptual multistability and experiments on continuous perception in general.

The package is built using the Stan probabilistic programming language (Carpenter et al., 2017). Thus, it provides posterior distributions, the ability to compare models via information criteria (Vehtari et al., 2017), etc. In addition, the package provides Stan code for performing the estimation and an example that explains how to implement a custom Stan model that relies on it. The source code for `bistablehistory` has been archived to Zenodo with the linked DOI: Pastukhov (2021).

Statement of Need

Analysis of time series from psychophysical experiments, particularly on multistable perception, frequently requires taking into account the slow accumulation of adaptation. R has an extensive toolset for working with time-series, e.g., see cran.r-project.org/web/views/TimeSeries.html, using frequentist (Hyndman & Khandakar, 2008) and Bayesian (Alonzo & Cruz, 2020) approaches. The purpose of *bistablehistory* package is to extend the existing tools by incorporating fitting of cumulative history via a homogeneous first-order process, which is more accurate (Pastukhov & Braun, 2011) than commonly used approximation via an autocorrelation coefficient (Ee, 2009). The package simplifies both computing cumulative history and its use directly as part of a statistical (generalized) linear model fitted by a package function.

Cumulative history computation

The cumulative history for a perceptual state is computed via a homogeneous first-order process (for details on first order linear differential equations, please refer to chapter 2 in Wilson (1999)):

$$\frac{dh_i}{dt} = \frac{1}{\tau}(-h_i + S_i(t)) \tag{1}$$

where τ is the time constant, h_i is cumulative history and $S_i(t)$ is the current signal level for the ith perceptual state, so that

$$S(t) = \begin{cases} 1 & \text{if state } i \text{ is dominant} \\ 0 & \text{if state } i \text{ is suppessed} \\ S_{mixed} & \text{if it is a mixed/transition phase and } 0 S_{mixed} 1 \end{cases} \tag{2}$$

where S_{mixed} corresponds to the `mixed_state` parameter that can be either specified (the `fit_cumhist()` function uses a default of `0.5`) or fitted. The general solution for the equation (see Theorem 1 in Wilson (1999), chapter 2, page 15) is

$$h_i(t) = Ae^{-t/\tau} + \frac{1}{\tau}\int_0^t e^{-(t'-t)/\tau}S(t')dt' \tag{3}$$

where A is chosen to satisfy the initial condition. Assuming a constant signal S, we obtain

$$h_i(t) = Ae^{-t/\tau} + S_i \cdot (1 - e^{-t/\tau}) \tag{4}$$

For the cumulative history, we are interested in $h_i(t + \Delta t)$: a change following a dominance phase that starts at time t, ends at time $t + \Delta t$, and has a constant signal strength S_i. Assuming that a dominance phase starts at $t = 0$ and substituting into the equation 4, $h_i(0) = A$. In other words, constant A is equal to cumulative history state before the dominance phase onset and, therefore, the relative signal strength during the dominance phase is determined by the difference between the signal strength and the initial cumulative history value: $S_i - h_i(0)$. Thus

$$h_i(\Delta t) = h_i(0) + (S - h_i(0)) \cdot (1 - e^{-\Delta t/\tau}) \tag{5}$$

$$h_i(\Delta t) = S + (h_i(0) - S) \cdot e^{-\Delta t/\tau} \tag{6}$$

The figure below shows accumulation over time for three different initial values $(h(0))$, signal strength (S), and time constants (tau). Note that the package allows one to either specify and fit both the time constant (argument `tau` in `fit_cumhist()` function) and the initial history value at the block (`history_init` argument).
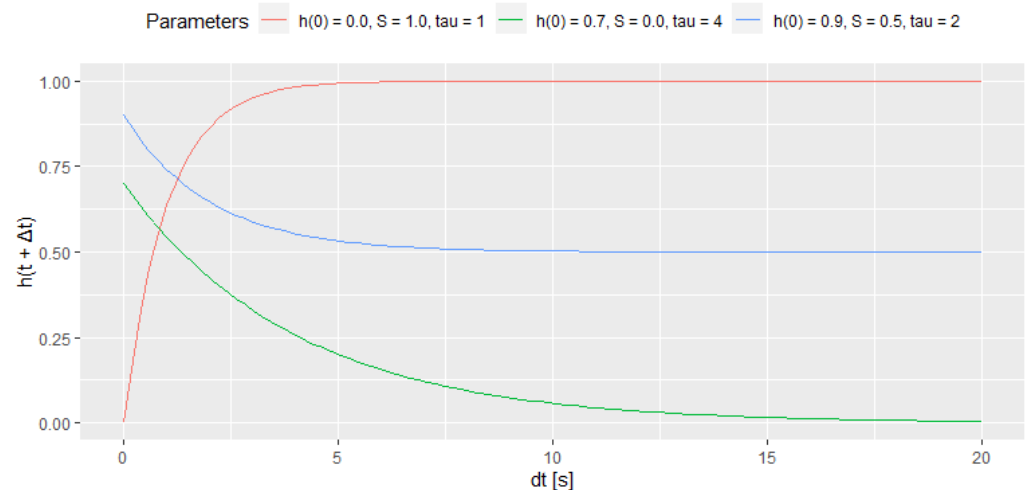

Figure 2: **Figure 2. Cumulative history for different initial conditions, signal strength, and time constants.**

For a bistable case, there are two history states, one for each perceptual state. Therefore, we compute a history as a difference of cumulative histories:

$$\Delta h(t, \tau) = h_{suppressed}(t, \tau) - h_{dominant}(t, \tau) \tag{7}$$

where $h_{dominant}$ and $h_{suppressed}$ are history states for currently dominant and suppressed states, respectively. *E.g.*, if a left eye dominates during the following phase, $h_{dominant} = h_{left}$ and $h_{suppressed} = h_{right}$ and vice versa.

Usage and Features

The main function is `fit_cumhist()`, which takes a data frame with time-series as a first argument. In addition, you need to specify the name of the column that codes the perceptual

state (`state` argument) and a column that holds either dominance phase duration (`duration`) or its onset (`onset`). The code below is the simplest case scenario, fitting data using the Gamma distribution (default family) for a single run of a single participant. By default, the function fits the time constant τ for slowly accumulating adaptation but uses default values for other parameters that influence history computation.

```
library(bistablehistory)
data(br_singleblock)
gamma_fit <- fit_cumhist(br_singleblock,
                         state="State",
                         duration="Duration",
                         refresh=0)
```

Alternatively, one can specify the *onset* of individual dominance phases to compute their duration.

```
gamma_fit <- fit_cumhist(br_singleblock,
                         state="State",
                         onset="Time")
```

Utility functions simplify extracting information about fitted parameters. For example, one can look at the fitted value for history time constant using `history_tau()`

```
history_tau(gamma_fit)
```

or the main effect of history for both parameters of gamma distribution via

```
historyef(gamma_fit)
```

extract an estimate of perceptual history / adaptation using `extract_history()` function

```
H <- extract_history(gam_fit)
```

or compute an expected duration for each dominance phase via `predict()`

```
br_singleblock$Predicted <- predict(gam_fit)
```

The package extends the analysis to multiple experimental runs (via the `run` argument that specifies a variable that identifies individual runs), to experimental sessions (via the `session` argument) that are assumed to have different average dominance phase durations (Suzuki & Grabowecky, 2007), and to multiple participants (via `random_effect` argument). It also allows incorporating fixed effects, although they are restricted to continuous metric variables (see a vignette on reusing model code directly in Stan for overcoming these limitations).

The example below demonstrates an analysis for many observers (`random_effect = "Observer"`) who performed multiple runs (`run = "Block"`) taking into account when the dominance phase occurred (`fixed_effects = "LogTime"`). It also uses custom prior for `tau` parameter and custom control parameters for the Stan sampler. Please refer to "Usage Examples" vignette for details on these and other settings.

```
library(bistablehistory)
library(tidyverse)

data(kde)
kde$LogTime <- log(kde$Time)
kde_fit <- fit_cumhist(kde,
                       state = "State",
                       duration = "Duration",
                       random_effect = "Observer",
                       fixed_effects = "LogTime",
                       run = "Block",
                       tau = "1|random",
                       history_priors = list("tau"=c(log(0.5), 0.3)),
                       chains = 4,
                       control = list(max_treedepth = 15,
                                      adapt_delta = 0.99))
```

Models fits can be compared via information criteria. Specifically, the log-likelihood is stored in a `log_lik` parameter that can be directly using `loo::extract_log_lik()` function (see package ([Vehtari et al., 2020](#))) or used to compute either a leave-one-out cross-validation (via `loo()` convenience function) or WAIC (via `waic()`). These are information criteria that can be used for model comparison the same way as Akaike (AIC), Bayesian (BIC), or deviance (DIC) information criteria. The latter can also be computed from log-likelihood, but WAIC and LOOCV are both recommended for multi-level models, see ([Vehtari et al., 2017](#)). The model comparison itself can be performed via `loo::loo_compare()` function from the `loo` package.

```
library(loo)
fit1 <- fit_cumhist(br_singleblock,
                    state="State",
                    onset="Time")

br_singleblock$LogTime <- log(br_singleblock$Time)
fit2 <- fit_cumhist(br_singleblock,
                    state="State",
                    onset="Time",
                    fixed_effects = "LogTime")

loo::loo_compare(list("null" = loo(fit1),
                      "+logTime" = loo(fit2)))
```

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