Ludwig-Maximilians-Universität
München
Department Biologie II Computational Neuroscience

Graduate School of
Systemic Neurosciences
LMU Munich

Report

Computational Simulation of Time Perception: Model Description and Implementation

Katharina Bracher
Student ID: 11754625

Supervision: Dr. Kay Thurley

Contents

1 Behavioral Effects in Magnitude Estimation

Magnitude estimation is subject to noise that arises from external sources i.e. the statistics of the environment and internal sources i.e. neural representation of the input and the behavior. Across sensory modalities, characteristic behavioral effects are identified (Petzschner et al. 2015). The most prominent observation is a regression to the mean of the stimulus range, i.e. small stimuli are overestimated whereas large stimuli are underestimated (*regression effect*). This effect intensifies for ranges with larger stimuli (*range effect*) For larger stimuli the standard deviation of estimates increases monotonically (*scalar variability*). Finally, the recent history of stimuli presentations influences the current stimuli estimation (*sequential effect*). All effects mentioned above are displayed in Fig. 1.

Modality-independence of these effects suggests the existence of a common underlying principle or processing mechanisms, that would explain e.g. a optimal strategy for unreliable judgments due to noise (in stimuli and estimates).

2 Model Description

Neural activity yields characteristic trajectories during time perception and time reproduction (Meirhaeghe et al. 2021, Wang et al. 2018, Henke et al. 2021). Flexible motor timing can be achieved by controlling the speed of neural dynamics (Sohn et al. 2019, Wang et al. 2018). Further, it has been found that neural

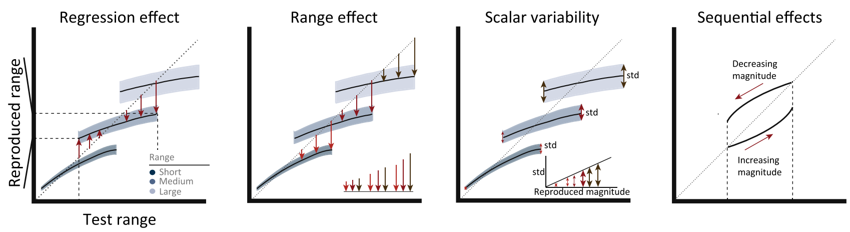

Figure 1: **Behavioral Effects** adapted from Petzschner et al. 2015.

activity in anticipation of a delayed response reaches a fixed threshold with rate inversely proportional to delay period Murakami et al. 2014, Mita et al. 2009). Wang et al. 2018 proposed a potential neural mechanism for speed control and based on that Egger et al. 2020 developed a neural circuit model for sensorimotor timing.

2.1 Circuit

Flexible speed control can be achieved by a simple model consisting of three units, u, v, y that represent population activity. Two units, u and v receive symmetric input I ($W_{uI} = W_{vI} = 6$) and have symmetric mutual inhibitory projections onto each other ($W_{uv} = W_{vu} = 6$). The inputs to u and v is governed by a sigmoidal activation function $\theta(x) = \frac{1}{1+exp(-x)}$ and all three units have a time constant $\tau = 100$. y is the output unit and receives excitatory input from u and inhibitory input from v ($W_{yu} = W_{yv} = 1$)which results in ramp-like behavior. Stochastic synaptic inputs are modeled as independent white noise η_u, η_v, η_y. The dynamics of u, v, and y are defined as follows:

$$\tau \frac{du}{dt} = -u + \theta(W_{uI}I - W_{uv}v + \eta_u) \tag{1}$$

$$\tau \frac{dv}{dt} = -v + \theta(W_{vI}I - W_{vu}v + \eta_v) \tag{2}$$

$$\tau \frac{dy}{dt} = -y + W_{yu}u - W_{yv}v + \eta_y \tag{3}$$

The speed at which the output y evolves can be controlled by the shared input to u and v (Fig. 2) (Egger et al. 2020) and determines the interval after which y reaches a fixed threshold y_0.

Depending on the input I, parameter and initial conditions, the system shows different dynamics. For low levels of I (0<I<0.5) the system has three fixed points (2 stable, 1 unstable at u=v) and y ramps up faster the higher the input I. For intermediate values of I (0.5<I<1) the system still shows three FP of the same sort and y ramps up with a slope that is inversely proportional to the input I (y ramps up slower the higher the input I, see Fig. 2b). For high I (1<I) the system has one stable fixed point (at u=v) and y ramps down faster for higher I. In this report, the intermediate input regime is explored. In this regime, higher an higher input I results in a smaller slope of y, such that the threshold y_0 is reached after a longer interval. Thus, input is controlling the speed of the dynamic.

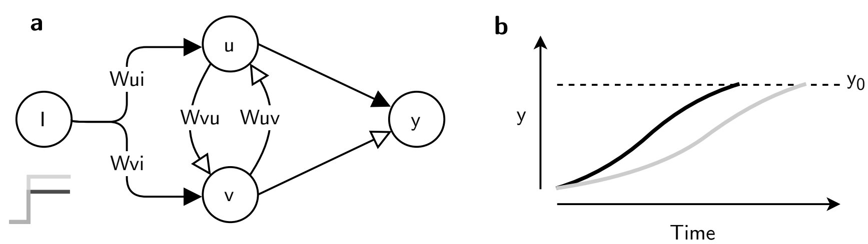

Figure 2: **Basic Circuit** adapted from Egger et al. 2020

Initial conditions of u, v and y have been optimized for in Egger et al. 2020 and are set to *xxx*.

2.2 Update Mechanism and Experiment simulation

Updating I based on feedback to adjust rate in reproduction stages: measurement, update and reset, reproduction until threshold update: delta y-th, weighted parameter: memory parameter K, reset, initial conditions, threshold timeouts

$$\tau \frac{du}{dt} = -u + \theta(W_{uI} I - W_{uv} v + \eta_u) \tag{4}$$

$$\tau \frac{dv}{dt} = -v + \theta(W_{vI} I - W_{vu} v + \eta_v) \tag{5}$$

$$\tau \frac{dy}{dt} = -y + W_{yu} u - W_{yv} v + \eta_y \tag{6}$$

3 Implementation of Model

3.1 Modules

Euler Implementation to Solve Differential Equation parallel Simulation experiment simulation update mechanism

3.2 Structure of Code

parallel simulations, experiment simulation

4 Results and Outlook

experiment simulation plot behavioral plot parameter search, extending units, neural trajectories

limitations and explorations regimes