MSc in Computational Cognitive Neuroscience

Goldsmiths
UNIVERSITY OF LONDON

Neural Implementation of Escape Decisions

Arriana Vararu & Dr. Sajjad Zabbah

Introduction

Escape behaviour is a crucial survival mechanism, yet its neural basis remains poorly understood. According to Evans et al. (2018), the drift diffusion model (DDM) provides a useful framework for explaining escape behaviour. Based on this model sensory evidence accumulates over time until a decision threshold is reached, at which point escape is initiated (Evans et al., 2018). The time taken to reach this threshold explains the variability in escape latency while the amount of evidence accumulated beyond the threshold accounts for differences in escape speed. Although this framework explains behavioural variability, how such processes are implemented in the brain is still unclear.

Wong & Wang (2006) introduced a biologically plausible neural implementation of DDMs using attractor dynamics, bridging the gap between abstract theories and applicable neural architecture. This model consists of computing neural populations that integrate inputs through mutual inhibition and self-excitation, forming stable activity patterns that guide a decision.
It remains an open question whether the neural implementation of drift diffusion models, such as attractor-based networks, can capture the full range of experimentally observed escape behaviours.

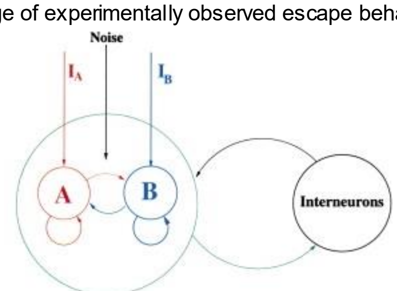


Figure 1. Diagram of attractor network from Wong & Wang (2006), showing two competing neural populations with self-excitation and mutual inhibition

Research Questions

Can an attractor-based neural model capture the variability and timing of escape decisions more accurately than a simple mean-response model, when fitted to behavioural data from mouse threat-response experiments?

Methods

We simulate escape decisions in MATLAB using an attractor-based model (Wong & Wang 2006), fitted to behavioural data from Evans et al. (2018). **Key parameters of the model and their behavioural correlates**

- **Input current** – threat intensity
- **Decision threshold** – speed accuracy trade-off
- **Neural noise** – attention
- **Synaptic weights** – behavioural dynamics

Modelling Phases:

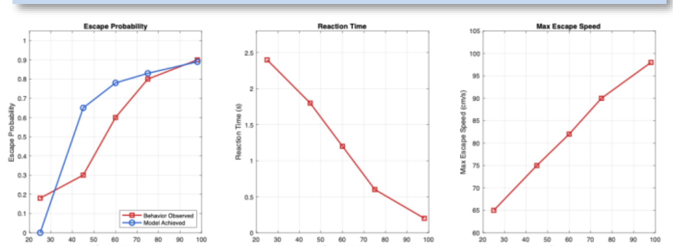
1. Model Setup – create an attractor network with two competing units and inhibitory interactions.

2. Parameter Tuning – adjust parameters systematically to align the model output with behavioural escape probabilities and timings.
3. Escape Speed Mapping – map the post-threshold firing rate to behavioural escape speed.

4. Evaluation – Compare attractor model to mean model on behavioural outputs using:
- R^2 goodness-of-fit
- Ability to predict escape speed

Hypotheses

1. The attractor-model will better predict escape probability as function of threat intensity compared to the mean model. (Graph a)
2. The model will generate reaction times that match more closely to the behavioural data than the mean model can. (Graph b)
3. The average firing rate after the decision threshold will correlate with escape speed (Graph c)



Graph a *Graph b* *Graph c*

Expected Results

Our preliminarily results (Graph a, the blue line) show that the model can replicate higher escape probability as a function of higher threat intensity creating a sigmoid shaped probability curves matching empirical data. These result were obtained using a blind search method in the parameter space; we expect further improvement with the use of appropriate optimization algorithms.
We also expect a decrease in escape time with increasing threat intensity, as per biological findings (Graph b). In addition, the model's suprathreshold firing rate is expected to correlated with escape speed (Graph c).

Finally, we believe that the proposed model will provide a plusible neural mechanism decision making under threat and advance our understanding of survival-related decision circuits. It may also enable the formulation of hypotheses about the neural basis of anxiety, particularly in cases where individuals overreact to minimally threatening situations.

for more, email: svara001@gold.ac.uk; s.zabbath@gold.ac.uk;

references: Evans et al. (2018); Wong & Wang (2006)