Models of Perceptual Uncertainty and Decision Making

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• How do we integrate sensory percepts?

• How do we weigh ambiguous evidence?
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• How do we weigh ambiguous evidence?
Vibrotactile experiment: perceptual decision making
Perceptual decision-making task

Vibrotactile discrimination task

Two-alternative forced choice:

1: Same or Different? S D
2: f2>f1?
Perceptual decision-making task

Vibrotactile discrimination task

Two-alternative forced choice:

1: Same or Different?
2: f2>f1? Y N
Perceptual decision-making task

Vibrotactile discrimination task

Two-alternative forced choice:

1: Same or Different? S D

2: f2>f1? Y N  Subtraction

Subtraction weighted by precision of stimulus representation
outline

• Same or Different? S D
  Effective connectivity
  Behavioral, fMRI, DCM

• f2>f1? Y N
  Time-order effect
  Behavioral, Bayesian approach
Vibrotactile discrimination task

Experiment 1: Same or Different?

Conditions:
1. Different or same frequencies – adaptation repetition suppression
Vibrotactile discrimination task

Conditions:
1. Different or same frequencies – adaptation
2. Pure or noisy sinusoidal shape –
   what is the role of noise in the input frequency?
Vibrotactile discrimination task

Conditions:
1. Different or same frequencies – adaptation
2. Pure or noisy sinusoidal shape –

what is the role of noise in the input frequency?
Noise reduces precision of stimulus representation

Karim et al. 2012
Noise degrades the perception of different trials and improves the perception of same trials (interaction: $p=0.0007$, $F_{1,15}=17.927$)

Karim et al. 2014
Perceptual decision-making task

Inferior parietal lobe

Greater activity for different than for same input frequencies
Different > Same

A. Left Inferior Parietal Lobe

Inferior parietal lobe

Different > Same
Dorsal lateral prefrontal cortex

Different > Same
Rostral prefrontal cortex

Regular > Noisy
IPL (x1)
DLPFC (x2)
rPFC (x4)
SFG (x3)

Superior frontal gyrus
Interaction effect
Different > Same
A. Left Inferior Parietal Lobe

B. Left Frontal Middle Gyrus

IPL (x1)
DLPFC (x2)

Noise × Difference Interaction
Left Superior Frontal Gyrus

Regular > Noisy
Left Frontal Middle Gyrus (rostral PFC)

SFG (x3)
rPFC (x4)
Constellation of prefrontal regions
How do these regions interact?
Effective connectivity: Dynamic causal modelling

How do these regions interact?
Dynamic causal modelling

\[ \dot{x} = F(x, u, \theta) \]

neural state equation

\[ y = H(x, u, \theta) + \epsilon \]

hemodynamic state equations

Prediction

estimated BOLD response

forward model

Friston et al. (2003) Neuroimage
Dynamic causal modelling

\[
\dot{x} = F(x, u, \theta)
\]

\[
y = H(x, u, \theta) + \epsilon
\]

Model evidence

\[
p(y|m) = \int p(y|\theta, m) p(\theta|m) d\theta
\]

Probability of observing the data \(y\) given the model \(m\)

Model

Prediction

forward model

Empirical effect

model inversion

Friston et al. (2003) Neuroimage
Stephan et al. (2008) Neuroimage

effective connectivity
state changes
input

Bilinear state equation

\[ \frac{dx}{dt} = \left( A + \sum_{i=1}^{m} u_i B^{(i)} \right) x + Cu \]

Nonlinear state equation

\[ \frac{dx}{dt} = \left( A + \sum_{i=1}^{m} u_i B^{(i)} + \sum_{j=1}^{n} x_j D^{(j)} \right) x + Cu \]

state changes
modulation
input

effective connectivity
voltage dependent gating (via NMDA receptors)

Stephan et al. (2008) Neuroimage
Set of minimal models
Set of minimal models
Set of minimal models
Set of minimal models

Interaction

Different

Regular

Diamond
Set of minimal models

Serial
Set of minimal models

Parallel
Set of minimal models

Hierarchical (bilinear)
Set of minimal models

Hierarchical (nonlinear)
Example time series

Expectation maximisation optimises the posterior likelihood of each model given the data
Model comparison

Karim et al. 2014
The nonlinear hierarchical model which best describes the data

Karim et al. 2014
The nonlinear hierarchical model which best describes the data

How do these regions interact?

Karim et al. 2014
outline

• Same or Different? Effective connectivity
  Behavioral, fMRI, DCM

• f2>f1? Time-order effect
  Behavioral, Bayesian approach
Modeling time-order effect

Delayed vibrotactile discrimination task
Modeling time-order effect

Delayed vibrotactile discrimination task

f1=A; f2=B

f1=B; f2=A

Accuracy AB ≠ Accuracy BA
Modeling time-order effect

Delayed vibrotactile discrimination task

\[ f_1 = A; f_2 = B \]

\[ f_1 = B; f_2 = A \]

Accuracy AB

Accuracy BA ≠ Accuracy AB

Time-order effect
Modeling time-order effect

Delayed vibrotactile discrimination task

Preferred order improves accuracy

Global mean = 34 Hz

Karim et al. 2013
Modeling time-order effect

Delayed vibrotactile discrimination task

Preferred order improves accuracy
Nonpreferred order reduces accuracy

Global mean = 34 Hz

Karim et al. 2013
Bayesian approach

\[ p(x|s) = p(x) \frac{p(s|x)}{p(s)} \]
Bayesian approach

Gaussian assumption:

\[ p(x|s) = p(x) \frac{p(s|x)}{p(s)} \]

Prior belief:

\[ p(x) = \frac{1}{\sqrt{2\pi\sigma_0}} \exp \left( -\frac{(x-x_0)^2}{2\sigma_0^2} \right) \]

Likelihood:

\[ p(s|x) = \frac{1}{\sqrt{2\pi\sigma_s}} \exp \left( -\frac{(x-x_s)^2}{2\sigma_s^2} \right) \]

Posterior belief:

\[ p(x|s) = \frac{1}{\sqrt{2\pi\sigma}} \exp \left( -\frac{(x-\hat{x})^2}{2\sigma^2} \right) \]
Bayesian approach

Gaussian assumption: \( p(x|s) = \frac{p(x) \ p(s|x)}{p(s)} \)

Prior belief: \( p(x) = \frac{1}{\sqrt{2\pi\sigma_0}} \exp \left( -\frac{(x-x_0)^2}{2\sigma_0^2} \right) \)

Likelihood: \( p(s|x) = \frac{1}{\sqrt{2\pi\sigma_s}} \exp \left( -\frac{(x-s_x)^2}{2\sigma_s^2} \right) \)

Posterior belief: \( p(x|s) = \frac{1}{\sqrt{2\pi\sigma}} \exp \left( -\frac{(x-\hat{x})^2}{2\sigma^2} \right) \)
Without precision fade

\[ p(x|s) = p(x) \cdot \frac{p(s|x)}{p(s)} \]

Preferred order

Posterior belief (f1)

Sensory evidence – likelihood (f1)

Prior belief

\( f_1 = 46 \text{ Hz} \)
Posterior belief (f1)

Prior belief

Sensory evidence – likelihood (f2)

Preferred order

\[
p(x|s) = \frac{p(x) \cdot p(s|x)}{p(s)}
\]
Posterior belief (f1)

Prior belief

f1=46 Hz

Posterior belief (f2)

Sensory evidence – likelihood (f2)

Preferred order

Posterior f1

Posterior f2

PC = 75%

p(x|s)=p(x) \frac{p(s|x)}{p(s)}

Without precision fade
Without precision fade

\[ p(x|s) = p(x) \frac{p(s|x)}{p(s)} \]

**Posterior belief (f1)**

**Posterior belief (f2)**

**Sensory evidence – likelihood (f2)**

**Preferred order**

**Posterior f1**

**Posterior f2**

**PC = 75%**

**Nonpreferred order**

\[ f1 = 46 \text{ Hz} \]

\[ f2 = 52 \text{ Hz} \]

\[ f1 = 52 \text{ Hz} \]
Without precision fade

\[ p(x|s) = p(x) \frac{p(s|x)}{p(s)} \]

Posterior belief (f1)

Posterior belief (f2)

Sensory evidence – likelihood (f2)

Preferred order

PC = 75%

Nonpreferred order

f1 = 46 Hz

f2 = 52 Hz

f1 = 52 Hz

f2 = 46 Hz

PC = 75%
Without precision fade

\[ p(x|s) = p(x) \frac{p(s|x)}{p(s)} \]

- Posterior belief (f1)
  - Prior belief
  - Posterior belief (f1)
  - Sensory evidence – likelihood (f2)
  - Posterior belief (f2)
- Posterior f1
  - Posterior f2

Preferred order
- PC = 75%

Nonpreferred order
- PC = 75%

- f1=46 Hz
- f2=52 Hz
- f1=52 Hz
- f2=46 Hz
The variance of the sensory evidence of stimulus f1 grows in time
The variance of the sensory evidence of stimulus f1 grows in time.
\[ p(x|s) = \frac{p(x) \cdot p(s|x)}{p(s)} \]

Preferred order

Posterior f1

Posterior f2

PC = 79%

f1 = 46 Hz

f2 = 52 Hz
Precision fade

\[ p(x|s) = \frac{p(x)p(s|x)}{p(s)} \]

\[ f_1 = 46 \text{ Hz} \]
\[ f_2 = 52 \text{ Hz} \]

Posterior f1
Posterior f2

PC = 79%
\[ p(x|s) = \frac{p(x) \cdot p(s|x)}{p(s)} \]

**Precision fade**

- **f1** = 46 Hz
- **f2** = 52 Hz
- Posterior f1
- Posterior f2
- PC = 79%

**Preferred order**

**Nonpreferred order**

- **f1** = 52 Hz, **f2** = 46 Hz
- Posterior f2
- Posterior f1
- PC = 64%
Karim et al. 2013
data

Accuracy

Prop. correct

\[ f_2 > f_1 \text{ ‘faster’} \]

\[ f_2 < f_1 \text{ ‘slower’} \]

Langdon et al. 2012
Data

Accuracy

Model

- For $f_2 > f_1$ ('faster'), the accuracy decreases.
- For $f_2 < f_1$ ('slower'), the accuracy increases.

PC (%) vs. $f_1$ (Hz)
Conclusions

- Vibrotactile decision-making task depends on a constellation of prefrontal cortical areas

- The data is best described by nonlinear hierarchical models

- Time-order effect = estimation + precision fade
Thank you
Thank you
The nonlinear term in the D matrix embodies a very basic form of neurophysiological gating, namely voltage dependent gating via NMDA receptors.