

# Outline: Cue Integration in Motor Control

## DAY 1: LECTURES

### I. Basics of sensory cue integration

- A. Independent unbiased cues, minimize variance -> cue weights and reliability  
Landy, Maloney, Johnston & Young (1995). *Vis Res*, 35, 2863-2877.
- B. Introduction to Bayesian estimation: Likelihoods, priors, ML, MAP, cost functions, examples including signal detection and criterion  
Mamassian & Landy (1998). *Vis Res*, 38, 2817-2832.  
Mamassian & Landy (2001). *Vis Res*, 41, 2653-2688.
- C. Bayesian Gaussian MAP case (math)

### II. Basic psychophysics of sensory cue integration

- A. Perturbation analysis
- B. Basic psychophysical results  
Young, Landy & Maloney (1993). *Vis Res*, 33, 2685-2696.  
Landy & Kojima (2001). *JOSA A*, 18, 2307-2320.  
Ernst & Banks (2002). *Nature*, 415, 429-433.  
etc,

### III. Optimality applied to visually guided movement

- A. Movement under risk  
Trommershäuser, Maloney & Landy (2003). *JOSA A*, 20, 1419-1433.
- B. Motor cost functions  
Körding & Wolpert (2004). *PNAS*, 101, 9839-9842.
- C. The general case of optimizing choice of movement plan
- D. Aside: vector vs. endpoint codes for planning movement: learning and adaptation  
Hudson & Landy (2012). Work both under review and in prep.  
Hudson & Landy (2012). *J Neurosci Meths*, 208, 48-58.
- E. Movement planning as “method integration”

### IV. Nonlinearities and other complexities

- A. Correlated cues  
Oruç, Maloney & Landy (2003). *Vis Res*, 43, 2451-2468.
- B. Resolving ambiguity and cue promotion, Bayesian version  
Book's example: Saunders & Knill (2001). *Vis Res*, 41, 3163-3183
- C. Robust estimation — basic idea
- D. Robust estimation and long-tailed priors  
Knill (2003). *Vis Res*, 43, 831-854.
- E. Causal inference take I: common or separate source, review of ventriloquist, flash-beep, size estimation  
Körding, Beierholm, Ma, Quartz, Tenenbaum & Shams (2007). *PLoS One*, 2(9), e943.

Shams, Ma & Beierholm (2005). *Neuroreport*, 16, 1923-1927.  
Gepshtein, Burge, Ernst & Banks (2005). *J Vis*, 5, 1013-1023.  
F. Mandatory cue integration, visual metamers  
Hillis, Ernst, Banks & Landy (2002). *Science*, 298, 1627-1630.

V. Motion integration as cue integration

Adelson & Movshon (1982). *Nature*, 300, 523-525.  
Movshon, Adelson, Gizzi & Newsome (1985). In C. Chagas, R. Gattass & C. Gross (Eds.), *Pattern Recognition Mechanisms, Pontificiae Academiae Scientiarum Scripta Varia*, 54, 117-151.  
Weiss, Simoncelli & Adelson (2002). *Nat Neurosci*, 5, 598-604.

**DAY 1: EXERCISES:**

**EXERCISE 1: WEIGHTS VS. RELIABILITY — INDEPENDENT VS. CORRELATED CUES**

Goal is to illustrate the basic properties of statistical combination, and the connection between weights, independence and Gaussianity. This can be done in closed form or by simulation if you find that more enlightening. (A) Generate a plot of reliability (alternatively: variance of the estimate) for weighted averages of two cues (with reliabilities in proportion 1:2, for example) as a function of the weight on the first cue. (B) Repeat for two cues that are correlated, trying both low correlation coefficients (e.g., 0.2) and high (e.g., 0.8). Note: to generate two zero-mean, unit variance random variables with correlation  $\rho$ , as Flip mentioned, in Matlab:

```
sqrtn([1 rho^2; rho^2 1])*randn(2,1)
```

**EXERCISE 2: ILLUSTRATION OF GAUSSIAN ESTIMATION USING DATA FROM KÖRDING AND WOLPERT**

Fit the end points, show the effect that priors have by replicating one of Körding & Wolpert's plots

**EXERCISE 3: ILLUSTRATION OF CUE COMBINATION — DEMO**

Collect (and presumably share) a dataset of the demonstration experiment based on Landy & Kojima (2001). Plot the psychometric functions, fit curves to estimate points of subjective equality (PSE). Plot PSE as a function of cue shift and estimate cue weights.

**EXERCISE 4: MOTION INTEGRATION**

## DAY 2: LECTURES

### VI. Causal inference take II: Complex generative models

#### A. Explaining away ...

Knill & Kersten (1991). *Nature*, 351, 228-230.

Battaglia, Di Luca, Ernst, Schrater, Machulla & Kersten (2010). *PLoS Comp Biol*, 6(3), e1000697.

Battaglia, Schrater & Kersten (2005). *Proc. 2nd Symp Appl Perc, Graphics, Visualization*. ACM, 95, 145-152.

#### B. General Gaussian algebra (addition, convolution, etc.)

Bishop (2006). *Pattern Recognition and Machine Learning*. Springer.

Battaglia reanalysis using multivariate Gaussians.

### VII. Integration over time

#### A. Diffusion models (e.g., diffusion to bound models of decision making)

Shadlen/Newsome refs

#### B. Kalman filters

Baddeley, Ingram & Miall (2003). *J Neurosci*, 23, 3066-3075.

Burge, Ernst & Banks (2008). *J Vis*, 8(4):20, 1-19.

Haith, Jackson, Miall, Vijayakumar (2009) *NIPS*, 21, 593-600.

Vijayakuma, Hospedales & Haith. In Trommershäuser, Körding & Landy (Eds.), *Sensory Cue Integration* (pp. 63-81). New York: Oxford.

Wolpert, Ghahramani & Jordan (1995). *Science*, 269, 1880-1882.

Motion extrapolation preprint, Fulvio and Schrater

### VIII. Learning Cue integration, likelihoods, uncertainty, priors and weights

#### A. Learning likelihoods: Estimation of uncertainty, variable cue weights in a visual scene

Trommershäuser, Gepshtein, Maloney, Landy & Banks (2005). *J Neurosci*, 25, 7169-7178.

Hudson, Tassinari & Landy (2010). *PLoS Comp Biol*, 6(11), e1000982.

Landy, Trommershäuser & Daw (in press). *J Neurosci*.

Hillis, Watt, Landy & Banks (2004). *J Vis*, 4, 967-992.

#### B. Learning a prior

Seydell, Knill & Trommershäuser (2010). *J Vis*, 10(4):1, 1-27.

#### C. Cue calibration, should it be based on cue reliability

Burge, Girshick & Banks (2010). *J Neurosci*, 30, 7714-7721.

Ernst & Di Luca (2011). In Trommershäuser, Körding & Landy (Eds.), *Sensory Cue Integration* (pp. 224-250). New York: Oxford.

#### D. When is an error relevant? When does it drive adaptation?

Wei & Körding (2009). *J Neurophysiol*, 101, 655-664.

Srimal, Diedrichsen, Ryklin & Curtis (2008). *J Neurophysiol*, 99, 1554-1558.

#### E. Learning likelihoods: Relations between cues, attributes and sensory data.

Sahani & Whitely (2011). In Trommershäuser, Körding & Landy (Eds.), *Sensory Cue Integration* (pp. 82-100). New York: Oxford.

Michel & Jacobs (2008). *J Vis*, 8(2):3, 1-16.  
Manifold learning example on faces.

## DAY 2: EXERCISES

EXERCISE 5: Basic properties of multivariate Gaussians, marginalization, conditioning and combination.

EXERCISE 6: Kalman filter simulations of trajectory motion — setting up the dynamics, measurement, and noise matrices. Propagating predictions with missing data (occlusion).

EXERCISE 7: Learning cues in new domains. I will have set up 1) a set of aligned face images with attractiveness ratings. 2) manifold coordinates for each image  $\mathbf{s}$ , using the two manifold dimensions  $\mathbf{c}$  most correlated with attractiveness ratings  $\mathbf{a}$ .

Project goals:

- 1) develop a conditional Gaussian model  $P(\mathbf{c} | \mathbf{a})$  which captures the dependence between cues and attractiveness. (possibly do the  $\mathbf{c} \rightarrow \mathbf{x}$  reconstructions to show what the cues mean, hope I have time)
- 2) estimate an a prior
- 3) Given coordinates  $\mathbf{c}$ , produce an estimate of  $\mathbf{a}$  based on the appropriate cue combination formulas.
- 4) Compute errors and reestimate cue reliabilities. How well does the model work?