A Bayesian Model of Multi-modal Visuomotor Adaptation

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Summary

- We propose a model of multi-modal adaptation of reaching movements based on optimal Bayesian inference of the causes of errors.
- Our model accounts for the patterns of trial-to-trial adaptation as well as perceptual aftereffects in vision and proprioception when visual feedback is shifted or rotated.

Motivation

Perceptual aftereffects of adaptation to shifted visual feedback

Many studies have reported that adaptation to shifted visual feedback induces shifts in both visual and proprioceptive perception [7, 2, 5].

- Subjects asked to locate a visual or proprioceptive (right fingertip) target with their unseen left fingertip.
- Persistent shift in perceived location of both visual and proprioceptive targets after exposure to shifted visual feedback.
- Visual shift aftereffect imposed shift.
- Some component of adaptation at the motor level.

Existing Models

Maximum Likelihood-Based sensor recalibration [1, 7]

- Discrepancy between vision and proprioception eliminated by adjusting each estimate towards max. likelihood estimate (MLE).
- Does not use knowledge of issued motor commands.
- No component of motor adaptation.
- Can plausibly be combined with a distinct motor adaptation model to fully describe trial-to-trial behaviour.

- Independent sensor calibration and motor adaptation.
- Tacitly assumed in [7] to infer relative precision of vision and proprioception.

- No direct experimental evidence to support independent sensor/motor adaptation.

Modelling Framework

Model of a generic visuomotor adaptation experiment

Simplified model of a single reaching trial under experimentally controlled conditions:

- Final hand position \( y \) depends on motor command \( u \), motor disturbance \( r \), and noise \( \eta \):

\[
y = u + r + \eta
\]

- \( \eta \) controlled via manipulandum, inertial load.
- \( \eta \)'s visual observation of hand position is noisy and shifted.

\[
y_{\text{obs}} = y + \varepsilon_{\text{obs}} + \varepsilon_{\text{prop}}
\]

- \( \varepsilon_{\text{obs}} \) controlled via prisms, virtual reality apparatus.
- Proprioceptive observation is also noisy and perturbed.

\[
y_{\text{prop}} = y + \varepsilon_{\text{prop}}
\]

- \( \varepsilon_{\text{prop}} \) manipulated by vibrations of muscles (less common).

- Equivalent assumptions are quite common in the motor adaptation literature, e.g. [7] (Vision/Proprioception model), [6] (Dynamics model).

Bayesian Adaptation Model

A unified approach to motor adaptation and sensor recalibration

Optimal joint inference of the three potential sources of systematic error.

- What the subject believes and observes:

\[
r_{t+1} = A r_t + \xi_t ; \quad \xi_t \sim N(0, Q)
\]

- Current beliefs about disturbance represented as a multivariate Gaussian:

\[
P(r|y_{t+1}, y_t) \sim e^{-\frac{1}{2}(r_t - r_{t+1})^T \Sigma^{-1}(r_{t+1} - r_{t})}
\]

- Motor commands chosen on each trial according to most likely set of disturbances:

\[
\text{subject infers posterior estimate of the disturbances given new observations from each trial, motor commands issued, and prior beliefs (posterior from previous trial)}
\]

- Equivalent to a Kalman filter with latent state variable with estimated disturbance.

\[
\text{Subject maintains a statistical estimate of the total disturbance } r_t = (r^v_t, r^\sigma_t, r^\varepsilon_t)^T
\]

- New system model:

\[
x_t = o(x_{t-1}) + \varepsilon_t
\]

- Subject infers posterior estimate of the disturbances given new observations from each trial, motor commands issued, and prior beliefs (posterior from previous trial).

\[
\text{Subject maintains a statistical estimate of the total disturbance } r_t = (r^v_t, r^\sigma_t, r^\varepsilon_t)^T
\]

- System model:

\[
x_t = o(x_{t-1}) + \varepsilon_t
\]

- Observation noise:

\[
\text{Subject infers posterior estimate of the disturbances given new observations from each trial, motor commands issued, and prior beliefs (posterior from previous trial).}
\]

MLE-based Model Details

- MLE model is appropriate in large data set, e.g. human data.
- MLE model is appropriate in small data set, e.g. animal data.

Results

- Both models fitted to data using Matlab (lsqnonlin).
- Data taken from [4]:

- Reaching to 8 targets around a circle.
- Data represents average over cycle of 8 targets.
- Day 1 - Adaptation to 30° rotation of visual feedback.
- Day 2 - Restoring on same 30° rotation.
- Overnight forgetting model: \( r_{t+1} = Br_{t-1} \) (T = first trial of new day).

- Free parameters:

- Bayesian: \( \sigma^2_u, \sigma^2_v, \sigma^2_e, \lambda, \gamma, b \)
- MLE-based: \( \sigma^2_u, \sigma^2_v, \sigma^2_e, \beta, \gamma, b \)

Conclusions

- Unified approach to motor adaptation and sensor recalibration.
- Able to account for perceptual aftereffects of adaptation to shifted visual feedback.
- Multiple modelled disturbances leads to richer adaptation dynamics.
- Good agreement with experimental data.

- Bayesian model provides superior fit compared to MLE-based model.

Future Work

- Experimental testing of model predictions.
- Can changes in dynamics elicit perceptual aftereffects in the same way that shifted visual feedback can?
- Improved parameter estimation (EM-based).
- Extension to non-linear disturbances/adaptation.
- Different generalization patterns for kinematic vs dynamic disturbances.

References