Crossmodal conditioning to dynamic auditory-visual contingencies

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Using fMRI and dynamic causal modelling [1], we previously showed that the brain learns fixed probabilistic associations between simple auditory and visual stimuli, even when these stimuli are behaviourally irrelevant [2]. During learning, visual cortex activity and auditory-visual connectivity changed in accordance with the learning curve predicted by a Rescorla-Wagner (RW) model of associative learning. Here, we extend our previous study by (i) dynamically changing the statistical relationship between auditory and visual stimuli and (ii) using visual stimuli with a well-defined cortical representation (faces, houses). Subjects performed a speeded discrimination task on rapidly presented visual stimuli; on each trial, the visual stimulus was preceded by an auditory stimulus.

**Behavioural results:** Analyses of the reaction time (RT) data showed that the subjects' response latencies to the visual stimuli depended on the predictive value of the auditory stimuli (p<0.001), demonstrating that subjects could successfully track the underlying relationships. To investigate the dynamics of the subjects' online estimates of the cue-outcome association, we explored two basic learning models: (i) a classical RW model whose learning rate was obtained by maximum likelihood estimation from the measured RTs, and (ii) a simple ideal Bayesian observer hidden Markov model (HMM) representing the five levels of associative probabilities. Using the trial-by-trial estimates of the cue-outcome associations, as predicted by either of these learning models, the regression analyses explained a greater proportion of the variance in the RT data than using the true [but unknown] associations.

**fMRI results:** Generally, learning rate should depend on how quickly the environment is changing, i.e. its volatility. However, volatility-dependent changes in learning rates are not accommodated by the RW model nor by the ideal observer HMM. Therefore, we also used a three-level hierarchical Bayesian observer model (as in [3]) to predict the subjects’ online estimates of volatility. Using these volatility estimates as regressor in a general linear model of our fMRI data revealed a significant activation of anterior cingulate cortex (ACC; p<0.05, whole-brain corrected). Given previous results on volatility during reward learning [3], our findings suggest a general role of ACC in representing volatility, independently of the type of learning. In ongoing analyses we will characterize how volatility modulates the strength of effective connectivity amongst the brain regions activated by our paradigm.

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**References**

