Bayes on the court: Evidence for continuous prior-knowledge integration in virtual tennis returns

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Introduction

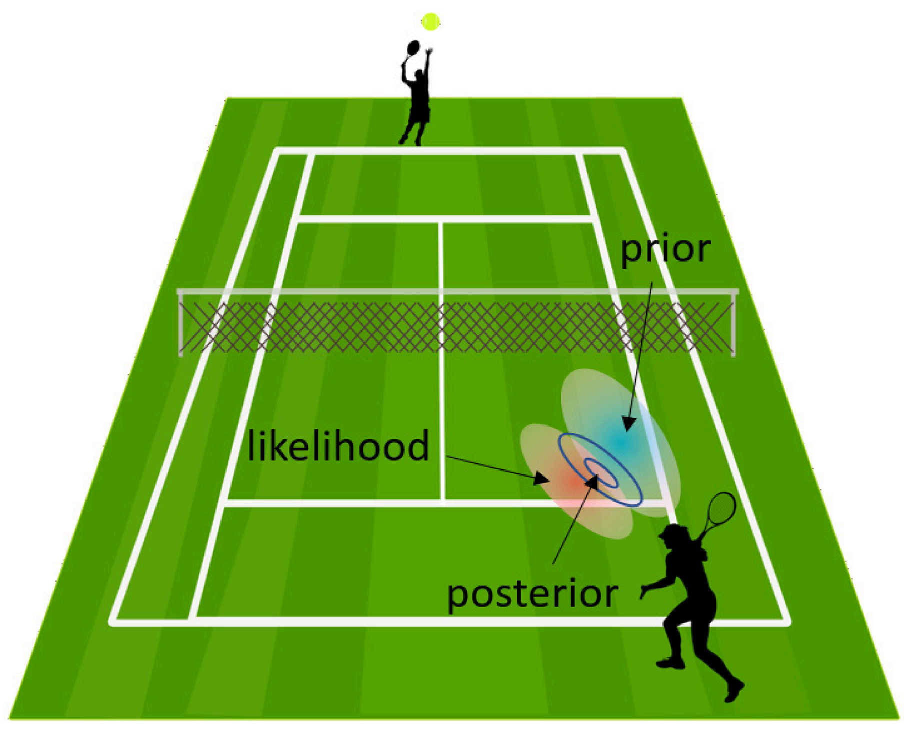


Figure adapted from Körding and Wolpert (2006, p. 320)

Recent decades of research suggest that humans integrate current sensory information and prior expectations in a **Bayesian way to guide behaviour**. However, while Bayesian integration provides a powerful framework for perception, cognition and motor control, evidence is largely limited to simple lab tasks so far (Beck et al., 2023). Here we provide evidence for core Bayesian predictions in a complex sensorimotor task at the limit of human performance: **returning tennis serves at a speed of 180 km/h or even 260 km/h**.

Methods and Results

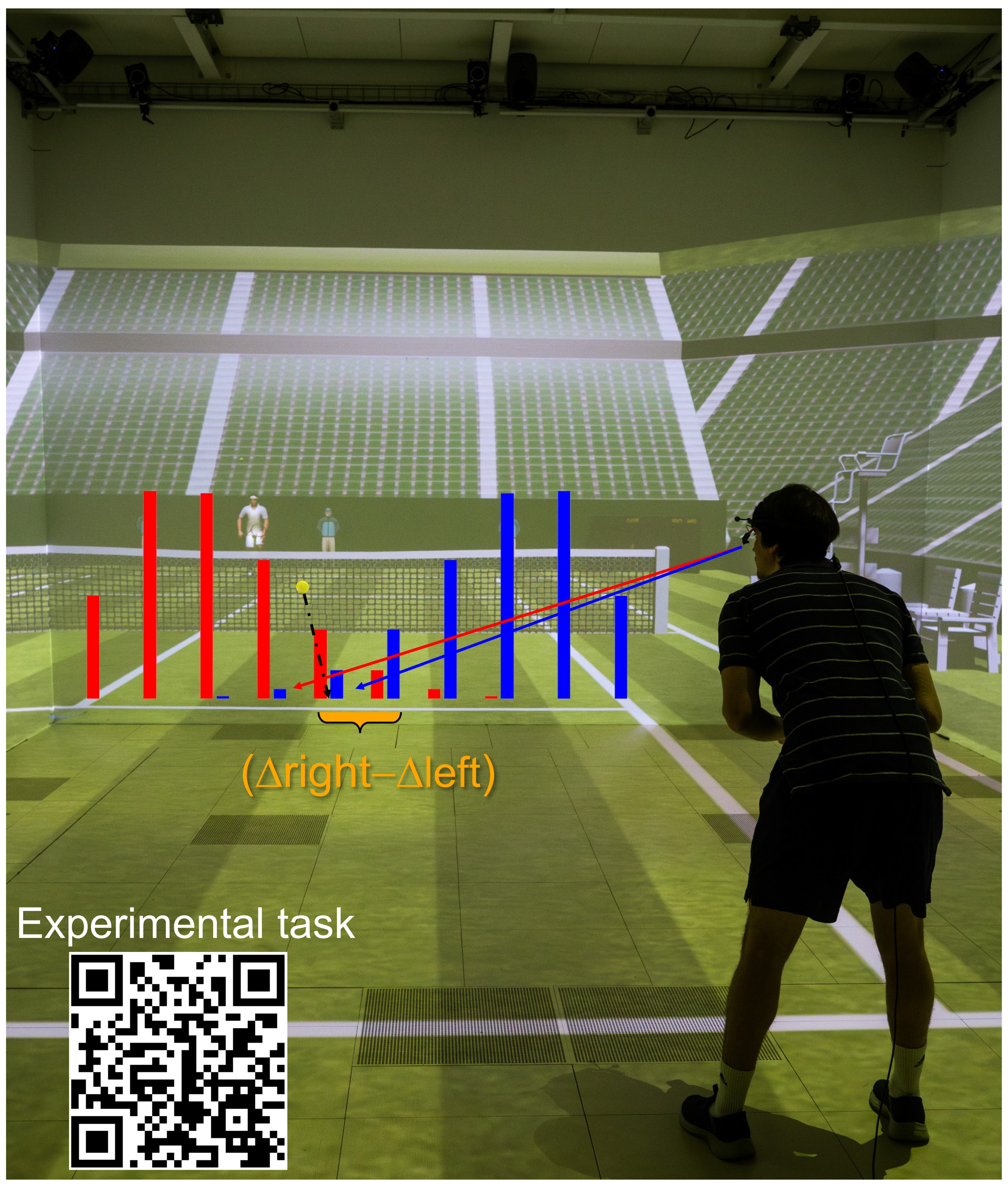
We manipulated serve locations:

- Probabilities of ball bouncing location in the left distribution (either on day 1 or day 2)
- Probabilities of ball bouncing location in the right distribution (either on day 2 or day 1)

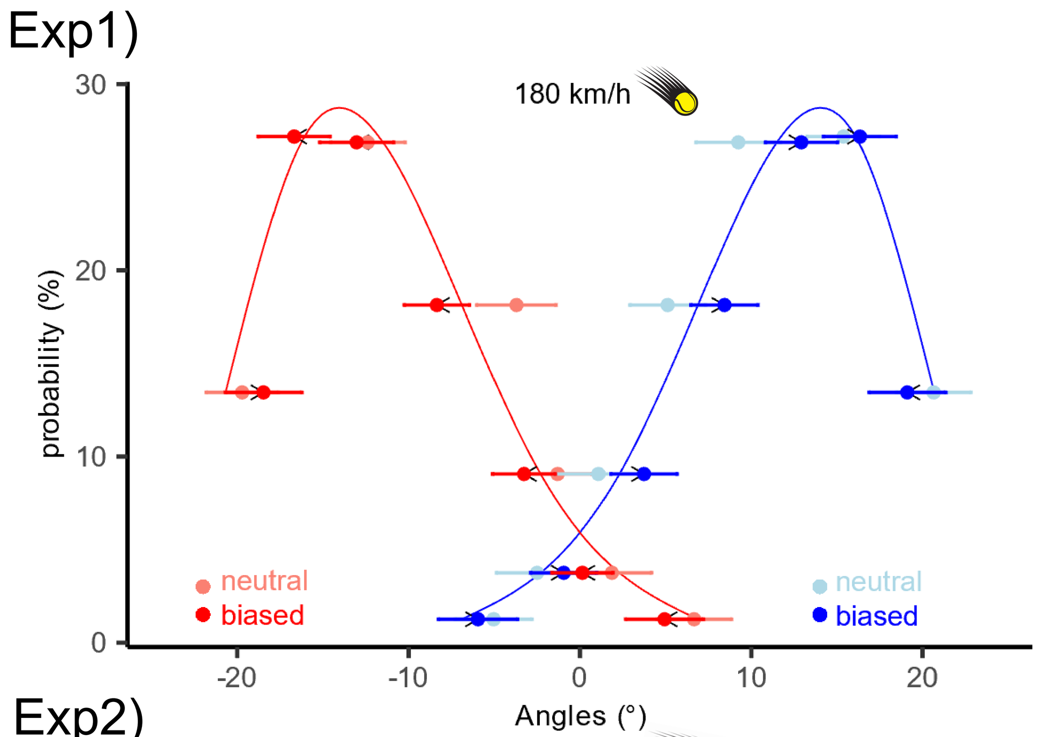
We measured:

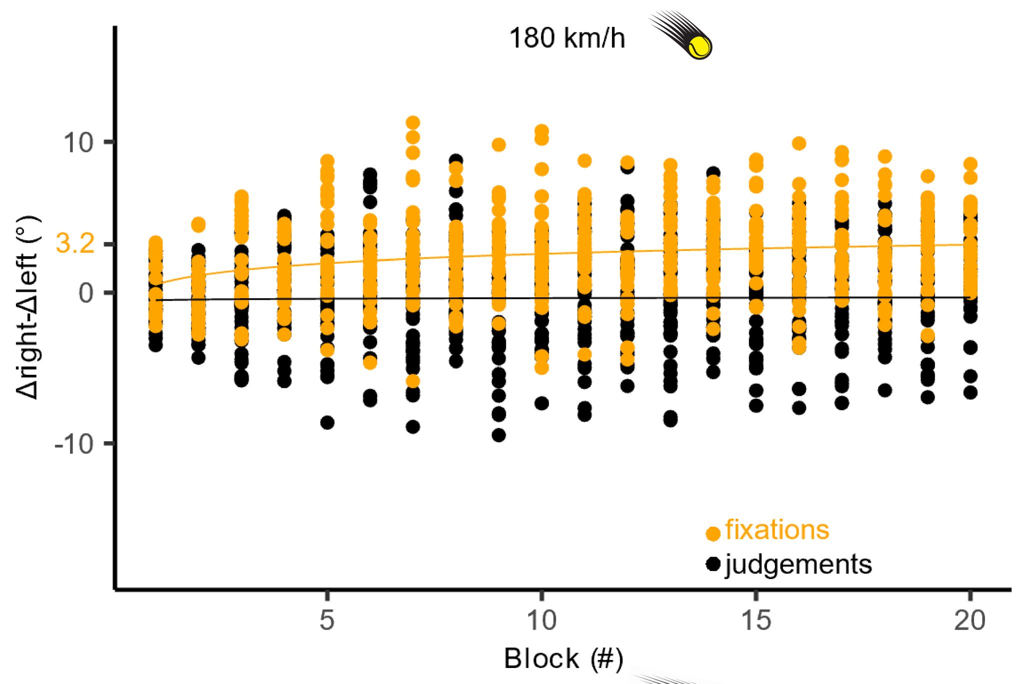
- Location of fixation after a predictive saccade → indicator for an estimate in action
- Explicit judgement of ball-bounce location → indicator for an estimate after the action

On two days with different serve-location probabilities (either left of right), manipulated in a VR setting, we measured **predictive gaze behaviour** to assess participants' in-action estimations of the ball-bounce location. Confirming Bayesian predictions, gaze was **biased towards the opponent's preferred serve locations**, particularly when visual uncertainty was increased by higher ball speeds. Beyond, we found a dynamic reliability-weighted integration on two timescales: **(1) The prior effect grew over the 'match'** (i.e. with increasing reliability of prior information). **(2) The prior affected early estimates of ball-bounce location** (i.e. gaze behaviour); **however, these estimates were gradually 'overwritten' by incoming sensory inputs** during ball flight.



Exp1)

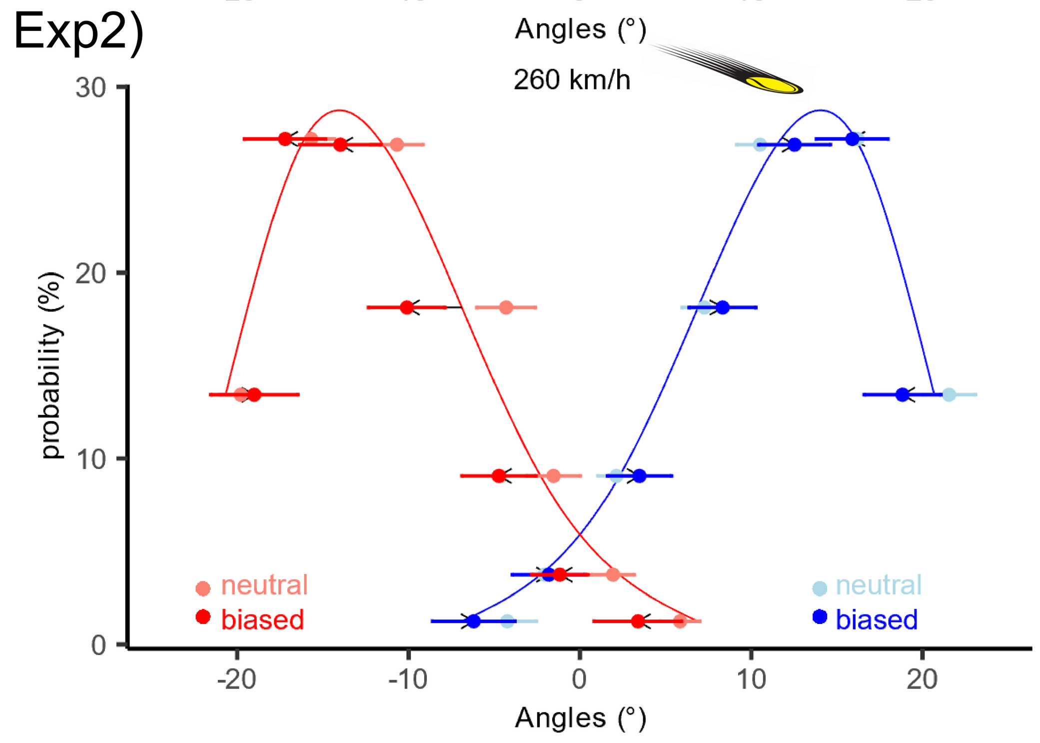


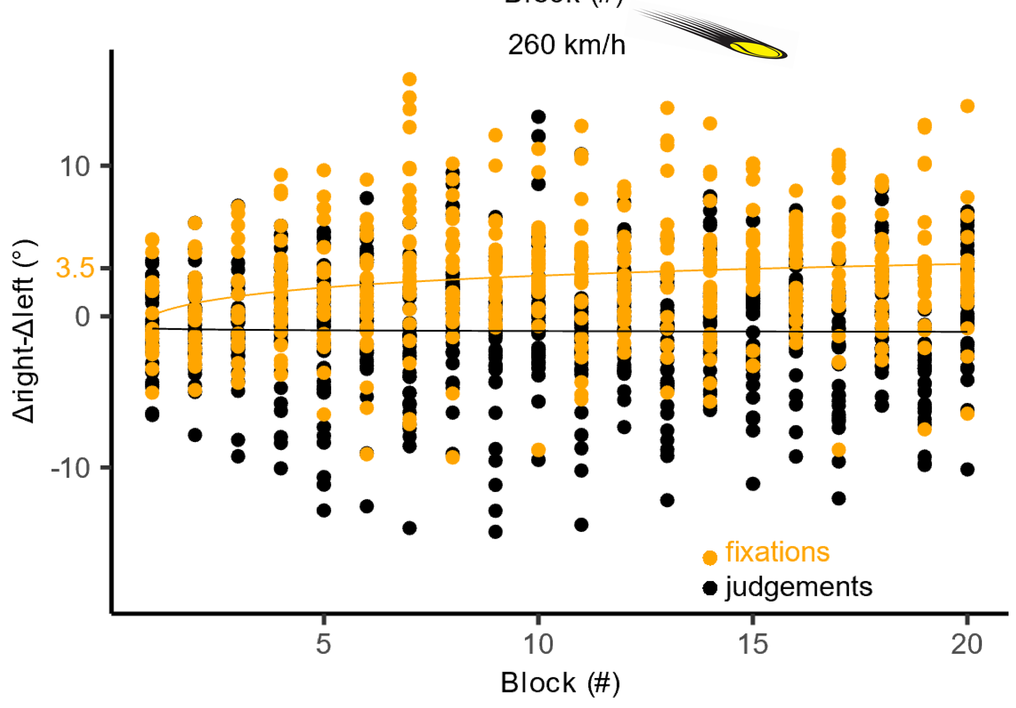


● $N_{subjects}$ = 32, $N_{measurements}$ = 533, **b = 0.88 [0.58 - 1.18]**, $p < .001$, $R^2_{marginal}$ = .050

● $N_{subjects}$ = 32, $N_{measurements}$ = 595, b = 0.06 [-0.28 - 0.40], p = .727, $R^2_{marginal} < .001$

Exp2)





● $N_{subjects}$ = 32, $N_{measurements}$ = 477, **b = 1.14 [0.70 - 1.57]**, $p < .001$, $R^2_{marginal}$ = .053

● $N_{subjects}$ = 32, $N_{measurements}$ = 619, b = -0.07 [-0.48 - 0.33], p = .727, $R^2_{marginal} < .001$

References

Beck, D., Hossner, E.-J. & Zahno, S. (2023). Mechanisms for handling uncertainty in sensorimotor control in sports: A scoping review. *International Review of Sport and Exercise Psychology*, 1–35.

Körding, K. P. & Wolpert, D. M. (2006). Bayesian decision theory in sensorimotor control. *Trends in Cognitive Sciences*, *10*(7), 319–326.