

1 **Rapid adaptive precision weighting in visual perception**

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3 William Turner<sup>1\*</sup>, Oh-Sang Kwon<sup>2</sup>, Minwoo JB Kim<sup>2</sup>, Hinze Hogendoorn<sup>1,3</sup>

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5 <sup>1</sup>Queensland University of Technology

6 <sup>2</sup>Ulsan National Institute of Science and Technology

7 <sup>3</sup>The University of Melbourne

8

9 \*Corresponding Author

10 William Turner

11 [williamfrancisturner@gmail.com](mailto:williamfrancisturner@gmail.com)

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21 **Abstract**

22

23 A striking perceptual phenomenon has recently been described wherein people  
24 report seeing abrupt jumps in the location of a smoothly moving object ('position  
25 resets'). Here, we show that this phenomenon can be understood within the  
26 framework of recursive Bayesian estimation as arising from transient gain  
27 changes, temporarily prioritising sensory input over predictive beliefs. From this  
28 perspective, position resets reveal a capacity for rapid adaptive precision  
29 weighting in human visual perception, and offer a possible testbed within which  
30 to study the timing and flexibility of sensory gain control.

31

32 **1. Introduction**

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34 Accurate visual localisation of objects is critical for adaptive behaviour, both  
35 evolutionarily (e.g., targeting prey while hunting) and in modern life (e.g.,  
36 navigating through traffic). However, there are instances where localisation goes  
37 awry. One of the most striking examples is the 'double drift' illusion, which occurs  
38 when a moving object contains internal motion in a direction orthogonal to its  
39 global trajectory (see Figure 1A; Lisi & Cavanagh, 2015). Under such conditions, if  
40 the object is viewed peripherally, extreme mis-localisations can occur.

41 Recently, it has been shown that the double drift illusion can be reset, such  
42 that people report seeing the object abruptly jump back toward its true position  
43 (Nakayama & Holcombe, 2020). These 'position resets' can be triggered by visual  
44 transients near the object and/or may occur spontaneously ('t Hart, Henriques, &  
45 Cavanagh, 2022). When asked to draw the (linearly moving) object's trajectory,  
46 participants draw a zig-zag shaped path (see Fig 1B).

47 Currently, the cause of position resets is unknown. One high-level account  
48 suggests that shifts of attention may somehow reset the perceived position of the  
49 object back to its veridical position (Nakayama & Holcombe, 2020). However, a  
50 computationally-rigorous account of this phenomenon is lacking, and the question  
51 of *why* attention might drive resets has not been addressed.

52 Here, we consider this phenomenon from the perspective of recursive  
53 Bayesian estimation, where perception is viewed as an unfolding inference  
54 process in which sensory inputs are combined with internally generated  
55 predictions, to derive more precise estimates of world states (e.g., an object's  
56 position and speed). From this perspective, we show that position resets can arise  
57 from transient gain changes which temporarily prioritise sensory input over  
58 predictive beliefs.

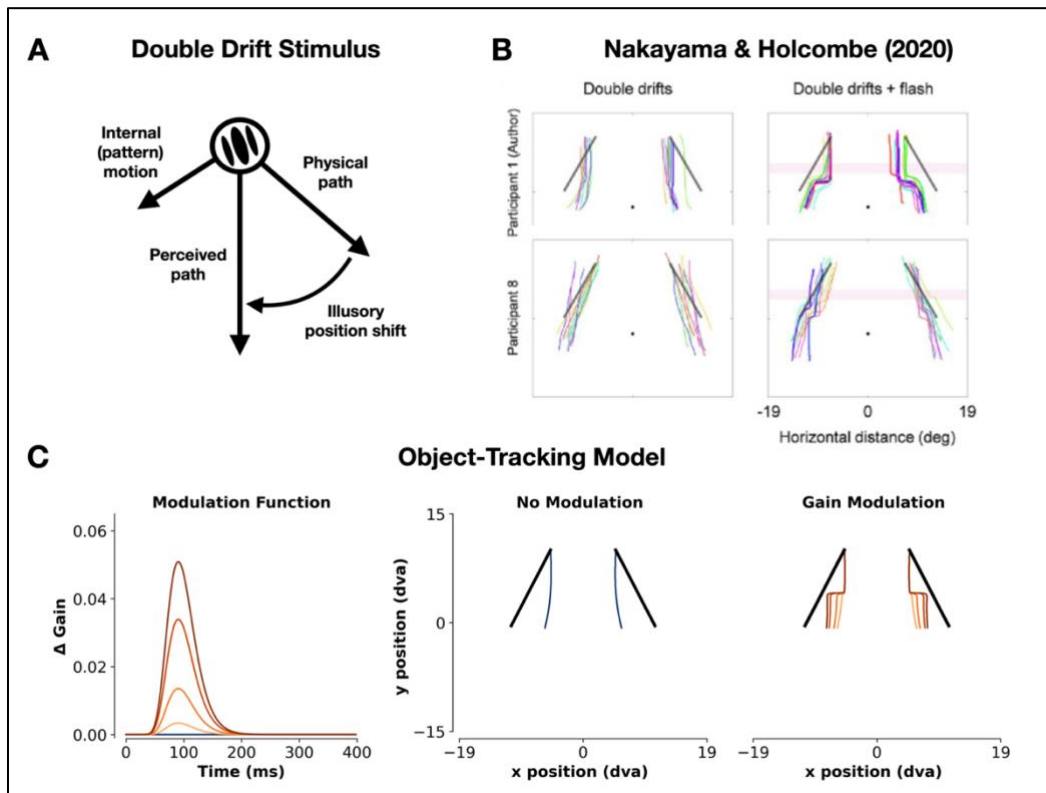
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60 **2. Model and Results**

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62 We simulated an object-tracking model previously used to account for a variant of  
63 the double drift illusion (the "curveball illusion"; for full model details see linked

64 code and Kwon et al., 2015). At its core is a generative model of motion dynamics  
 65 (i.e. the laws of motion) used to derive predictions about current world states.  
 66 That is, predictions are made about the current position and velocity of an object  
 67 given its past state. These are integrated with noisy sensory inputs to derive more  
 68 precise state estimates. This process takes the form of a Kalman Filter which is  
 69 optimal under the assumption of gaussian noise (Kalman, 1960).  
 70



71 **Figure 1. Accounting for 'position resets' in the double-drift illusion.** **A)** When  
 72 viewed peripherally, a diagonally moving Gabor stimulus can appear to travel  
 73 along a vertical path if its internal pattern (phase) moves in an orthogonal  
 74 direction. **B)** With brief flashes near the Gabor, participants report seeing abrupt  
 75 'position resets', such that the stimulus appears to move along a zig-zag shaped  
 76 path. Panels show hand-drawn stimulus trajectories from two participants viewing  
 77 double-drift stimuli with (right) and without (left) transient flashes (Nakayama &  
 78 Holcombe, 2020). With flashes, an abrupt kink can be seen midway through the  
 79 trajectories indicating that participants saw the stimulus jump back toward its true  
 80 position. **C)** A Bayesian object-tracking model (Kwon et al., 2015) gives a principled  
 81 account of this effect. Transient gain modulations (modelled via a log-normal  
 82 function with varying amplitude) drive the rapid re-weighting of inputs and  
 83 predictions within the model, resulting in a zig-zag shaped trajectory estimate.  
 84 Black diagonal lines indicate the true stimulus trajectories, blue lines show model

85 estimated trajectories under no gain modulation, and orange lines show model  
86 estimated trajectories under gain modulations of varying amplitude.

87

88 In the present simulations, we examined the effect of transient gain  
89 modulations on model-derived object trajectory estimates. Here, ‘gain’ refers to  
90 the weight given to incoming sensory information over predictive beliefs in  
91 determining the final state estimate. With higher gain, inputs are prioritised over  
92 predictions, and vice versa. Within the model, gain is calculated at each time point:

93

$$94 \quad K = PH^T(HPH^T + R)^{-1} + M$$

95

96 where P is the state covariance matrix, H is the observation matrix, R is the  
97 measurement noise covariance matrix, and M is an additive gain modulation  
98 matrix. To implement gain modulations, from 900 ms after stimulus onset we  
99 varied the diagonal of this matrix according to a log-normal function with varying  
100 amplitude (Figure 1C). Simulating modulations of varying strength, we found that  
101 transient gain modulations induced position resets. Stronger modulations  
102 triggered more abrupt resets, with model trajectory estimates qualitatively  
103 mirroring those from Nakayama and Holcombe (2020).

104 MATLAB and Python code for recreating these simulations is available at:  
105 <https://github.com/bootstrabill/position-reset-model>.

106

### 107 **3. Discussion**

108

109 We have given a computational account of ‘position resets’ in visual localisation  
110 (Nakayama & Holcombe, 2020). Through the lens of recursive Bayesian  
111 estimation, we have shown that resets can arise from gain modulations which  
112 temporarily prioritise sensory inputs over predictive beliefs. From this perspective,  
113 position resets reveal a capacity for rapid adaptive ‘precision weighting’ (Yon &  
114 Frith, 2021) in human visual perception.

115 Importantly, the current model is agnostic to the cause of gain changes. At  
116 least two hypotheses warrant investigation. First, attention shifts (either bottom-  
117 up or top-down) may ‘sharpen’ incoming sensory information (Nakayama &  
118 Holcombe, 2020). With increased precision, these inputs will be upweighted  
119 relative to predictions, triggering a reset. Second, abrupt visual transients may  
120 trigger a reduction in the precision of internally generated predictions (e.g.,  
121 ‘something has changed, so my predictions may no longer hold’). This too would  
122 lead to the prioritisation of inputs over predictions, and thus a reset. (For proof-  
123 of-principle simulations of these accounts see linked code.)

124

125 These accounts may not be mutually exclusive and could be further tested  
126 by examining whether resets are preceded by a sharpening of neural object  
127 position representations (Turner et al., 2023; Turner et al., 2024; Yon et al., 2018).  
128 As a general test of this perspective, studies could examine whether manipulations  
which increase sensory uncertainty (visual noise) can cancel out/prevent resets. If

129 this is possible, this would support the core idea that the relative precision of  
130 inputs and predictions ultimately determines their perceptual influence. With  
131 further support for this account, studies may also investigate the neurochemical  
132 basis of gain modulations. For example, by testing whether specific  
133 pharmacological interventions can inhibit/disrupt resets (Moran et al., 2013), or  
134 by studying pupil-linked arousal dynamics during spontaneous resets ('t Hart et al.,  
135 2022).

136 If resets reflect rapid precision weighting, then individual variability in this  
137 phenomenon should be examined. For example, studies could test whether  
138 certain clinical populations are resistant to experiencing resets, as this may be  
139 indicative of reduced perceptual flexibility – i.e., a ‘stubborn’ perceptual  
140 experience. Relatedly, individual differences in the double drift illusion have been  
141 observed to correlate with individual differences in the ‘twinkle goes’ and ‘flash  
142 grab’ illusions, suggesting they may share underlying mechanisms (Cottier et al.,  
143 2023). Future studies may therefore attempt to account for these illusions within  
144 the present framework. As a speculative example, in the twinkle goes illusion an  
145 increased reliance on predictions in the face of highly uncertain input (due to  
146 dynamic noise) may drive the lingering percept of the stimulus.

147 In sum, we have shown that ‘position resets’ can arise from transient gain  
148 changes, suggesting a capacity for rapid dynamic precision weighting in human  
149 visual perception. Future studies may further examine this phenomenon to better  
150 understand the temporal dynamics of sensory gain control.

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