Supplemental material

Introduction

In this section we describe some exploratory simulations that were carried out to address the following two issues:

(i) Can a simple integration to threshold mechanism account for the characteristics of the empirically derived temporal filter of Experiment 1?

(ii) Regardless of whether observers integrated sensory information up to some criterion level, did they integrate up to the saccadic dead time?

Before describing in greater detail exactly how we addressed these questions, we make a number of underlying assumptions of our approach explicit.

(i) The saccade latency period consists of a visual integration period and a nonvisual processing component.

(ii) The nonvisual processing component consists of a) a small initial delay before the integration starts, which leads observers not to process the first δ_{in} milliseconds of the stimulus, and b) the saccadic dead time, δ_{fin}, as discussed in the main paper. The initial delay can be regarded as an inability to optimally utilise the very first luminance sample of the stimulus (as indicated by the empirically derived temporal filter). This inability may relate, for example, to uncertainty regarding the time of stimulus onset (Luce, 1986). As a result of this uncertainty, the observer cannot perfectly anticipate when to start integrating the visual information. The signal to start integrating is the stimulus onset itself.

(iii) Integration is an all or none process: A time sample h is either included in the integration window (coded as 1) or not (coded as 0). This coding was conducted with millisecond resolution (i.e. h takes integer values from 1 to 1000).

(iv) Consider the logistic regression of the empirical data set. If a luminance sample at a particular instance of time *always* contributed to the decision process, the analysis would assign it a large weight. Conversely, if a luminance sample *never* contributed to the decision – such as samples occurring after the maximum saccade latency in a population – it would receive a weight of 0. This suggests a shortcut to determining the temporal weights: We simply count how often time sample h was included in the integration window across trials. This count is expressed of a proportion of the total number of simulated trials. Thus if a particular instance of time always contributes to the decision making process, it receives a weight of 1; if a sample never contributes to the decision its weight will be 0.

The first three assumptions are illustrated in Figure S1, which shows the integration window for one hypothetical trial.

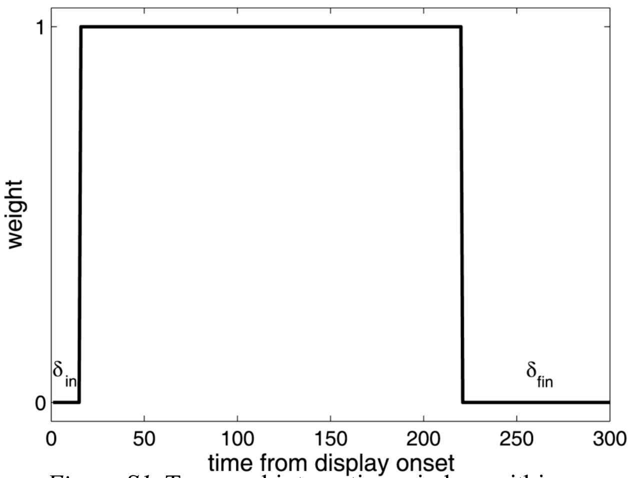

Figure S1. Temporal integration window within a 300 ms. fixation duration.

Integration to threshold model

Sequential sampling, or accumulator, models of various types have been very successful in accounting for both accuracy and latency data from 2 alternative perceptual choice experiments (Luce, 1986; Ratcliff and Smith, 2004). The model described in this section is based on the principles of this class of models in general, and on the diffusion model in particular (Ratcliff and Rouder, 1998; Ratcliff and Tuerlinckx, 2002). However, in the diffusion model processes such as stimulus encoding are lumped in a single parameter that is assumed to remain relatively constant. In this study we are precisely concerned with stimulus encoding and its link to decision making: The question is whether the visual stimulus is sampled until some criterion amount of evidence in favour of one or the other alternative is exceeded (Mazurek et al., 2003). This is a subtle, but important distinction.

As in the analysis of Experiment 1, we assume that observers integrate a signal that is the equivalent of the difference in luminance between the clockwise and anticlockwise patch. This decision variable will average 0.15 or -0.15 depending on whether the target is in the clockwise or anticlockwise position respectively. A value of 0 implies that there is no strong evidence in favour of either patch. As such, the integration starts from 0 and proceeds towards either an upper boundary, a, or a lower boundary, $-a$. These boundaries represent the criterion amounts of evidence that is required for a saccade to, respectively, the clockwise or anticlockwise patch.

The rate at which this decision signal is integrated depends on two factors: 1. the strength of sensory evidence – strong evidence in favour of one patch results in a shorter time period taken to cross a decision boundary, and 2. internal noise – at each time step h the integrated decision variable is perturbed by Gaussian distributed internal noise ($\mu = 0$). Internal noise is required for the model to generate error rates up to the level observed in our experiments. That is, even when the decision variable is generally positive within a trial and supports the presence of a clockwise target, the internal noise may drive the accumulation of evidence towards the lower decision boundary representing a saccade to the anticlockwise patch.

This model has 3 free parameters: the initial delay δ_{in}, the decision boundary a, and the amount of internal noise σ. The initial delay parameter refers to the width of a rectangular distribution ranging from 0 to δ_{in}. The shape of this distribution is not critical; the function of this parameter is simply to introduce a temporal weighting of the first stimulus sample that is about half the value of the highest weight. Inspection of Figure 2 of the main paper shows that this corresponds to the empirically observed pattern.

For each simulation the following steps were taken:

1. Each simulation consisted of 1000 trials. On half the trials, the target was in the anticlockwise position.
2. A decision variable matrix was constructed using the same procedure to draw Gaussian distributed random numbers as those that were used in the experimental program.
3. At each time step h the current value of the decision variable was perturbed by internal noise, and added to the integrated decision variable at time h-1.
4. As soon as the noisy integrated decision variable exceeded a or fell below $-a$, integration stopped.
5. After a thousand trials, the temporal weights were determined as described in assumption (iv) of the introduction. These weights were then sampled at

the same instances of time as the empirically derived temporal filter of Experiment 1.

6. These sampled weights were fitted with a log-Gaussian function.

We explored the parameter space in order to find a combination of parameters that resulted in error rates of ~20%, and temporal filter parameters within the range observed in Experiment 1. Having found such a combination of parameters, we repeated this sequence of steps 1000 times with this particular set of parameters to improve the reliability of our weight estimates. The temporal weights derived from each individual simulated experiment were averaged and fit with a log-Gaussian. The parameters of interest were the location and scale of the function. No attempt was made to minimise the error between the simulated temporal filter, and an empirically derived filter (e.g. the average filter of Experiment 1). The purpose of this exercise was simply to examine whether a simple integration to threshold model can produce the temporal impulse response that we derived.

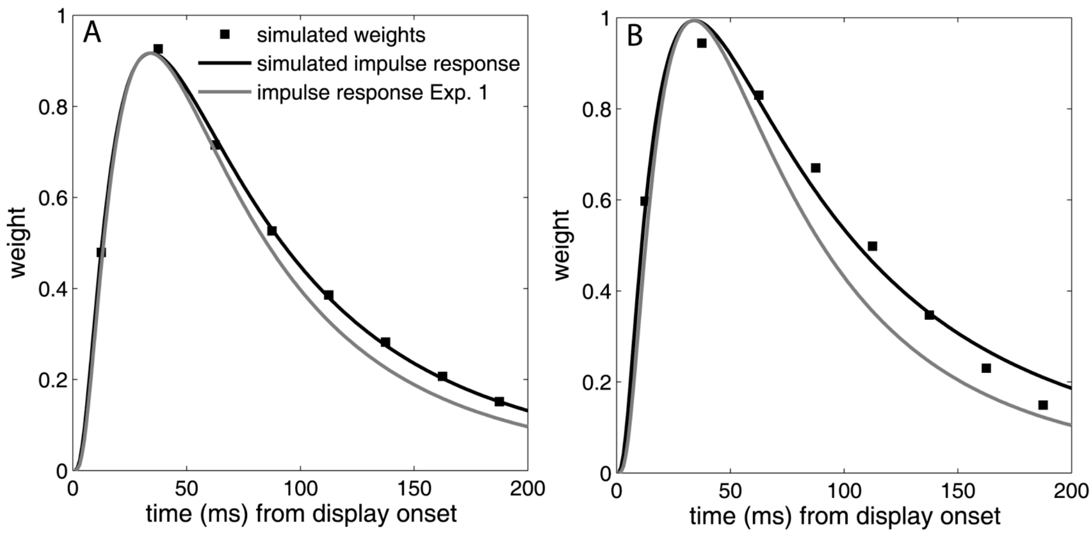

Figure S2. **A** – Temporal filter derived through simulations of the integration to threshold model. Model parameters were δ_{in} = 25, a = 25, σ = 2.4. **B** – Temporal filter derived through simulations of the integration to dead time model. Model parameters were δ_{in} = 20, δ_{fin} = 190, s = 80.

Figure S2A illustrates that this is indeed the case. The solid grey line corresponds to the empirical filter of Experiment 1, with the peak parameter set to the same height as the simulated impulse response, and the location and scale parameters set to the median values across the 4 observers. The average error rate over the 1000 simulated experiments was 21% (standard deviation ±1.28). Clearly it is possible for a very simple integration to threshold model to produce a temporal impulse response that is similar to our empirically derived filter, provided that the time to reach the threshold is relatively short (median integration period ~75 ms). However, this type of model cannot account for the empirical findings of Experiment 2 in the main paper.

Integration to dead time model

Our findings show that the visual signals in the first ~100 ms after display onset are driving the saccadic decisions in our paradigm. Given median saccade latencies on the order of 250 – 300 ms and an estimate of the saccadic dead time of ~80 ms, it appears that observers do not integrate the visual information up to the dead time. Before accepting this conclusion we sought to examine whether the empirically derived filter of Experiment 1 could be approximated by assuming that observers integrated up to the dead time, taking into account variability in the saccade latency and in the dead time component. In this simulation we are trying to answer the following question: If observers integrated information up to the dead time, what are the characteristics of the dead time that would result in pattern of weights observed in Experiment 1?

In these simulations we took a real saccade latency distribution (N=5755, from Observer 1 of Experiment 1). For each trial, we subtracted a dead time drawn from a uniform distribution with mean δ_{fin} and range s. Again, the precise form of this distribution is not critical for our purposes (we explored the consequences of a Gaussian distributed dead time and observed that the predictions were very similar). Including the initial delay parameter δ_{in}, there are 3 free parameters that can be adjusted to produce a temporal impulse response that approximates the one derived in Experiment 1.

Specifically for each simulation the following steps were taken:

1. One simulation consisted of the number of trials contained in the saccade latency distribution (N=5755).
2. For each saccade latency, the integration period corresponded to the latency minus the initial delay and the saccadic dead time. The initial delay was drawn from a uniform distribution ranging from 0 to δ_{in}. The dead time was drawn from a uniform distribution with mean δ_{fin} and range s.
3. After N trials, the temporal weights were determined as described in assumption iv of the introduction. These weights were then sampled at the

same instances of time as the empirically derived temporal filter of Experiment 1.

4. These sampled weights were fitted with a log-Gaussian function.

We explored the parameter space to find a combination of model parameters that produced a temporal filter with parameters close to those observed empirically. Again, no attempt was made to completely minimise the error between the simulated and observed filters. It turned out that a very close match was difficult to obtain: The mean dead time component, δ_{fin}, would have to be so large that on many trials it would exceed the observed saccade latency! After finding a set of model parameters that performed reasonably, we repeated the simulated experiment with this set of parameters 1000 times to improve the reliability of our temporal weights estimates. The averaged weights were fit with a log-Gaussian function, which is illustrated by the solid black line in Figure S2B. This simulated filter was obtained with δ_{fin} = 190. This estimate of the dead time is 2 – 3 times as large as the commonly accepted estimates that are on the order of 60 – 80 ms (Becker, 1991). Because this estimate of the dead time is so much longer than we would expect, this analysis confirms our view that observers were not integrating the visual information up to the dead time.

References

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