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# MODELLING THE MAINTENANCE OF VISUAL INFORMATION BEFORE CONSCIOUS PERCEPTION DURING METACONTRAST MASKING

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**Yota Kawashima**

Bernstein Center for Computational Neuroscience Berlin

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## ABSTRACT

How does the brain process visual stimuli and generate conscious perception? Psychophysical experiments provide insights into conscious visual perception. One such approach is metacontrast masking, where a target stimulus becomes invisible when followed by a mask stimulus delayed by approximately 40 ms. This suggests that the brain needs to maintain the target stimulus before conscious perception. It also suggests that the information maintenance can be interrupted by the mask stimulus. In this report, I aimed to develop a phenomenological model that replicates the metacontrast masking effect. I used 1) evidence accumulators to model target/mask stimulus encoding and 2) a leaky integrator to model the maintenance of the target stimulus information. The mask stimulus encoding leads to a negative impulse input to the leaky integrator, interrupting the information maintenance. Simulated data, after parameter tuning, showed that  $\sim 40$  ms delays made the masking effect stronger than shorter/longer delays, qualitatively replicating the masking effect.

## 1 Introduction

How does the brain process external visual information and generate conscious perception? Researchers have investigated conscious visual perception by using psychophysical techniques. For example, visual masking makes a target stimulus invisible by using a mask stimulus. This phenomenon provides insights into conscious visual perception [Breitmeyer and Öğmen, 2006, Kouider and Dehaene, 2007, Koch et al., 2016].

Metacontrast masking makes a target stimulus invisible by a delayed mask stimulus. For example, a grey disk stimulus (target) becomes invisible when it's followed by a black ring stimulus (mask) in about 40 ms delay (stimulus onset asynchrony, SOA) [Breitmeyer and Öğmen, 2006] (See Figure 1a and an online demo [https://run.pavlovia.org/Yota/standard\\_metacontrast](https://run.pavlovia.org/Yota/standard_metacontrast)). When the delay is too short or long, the disk stimulus is visible (Figure 1b).

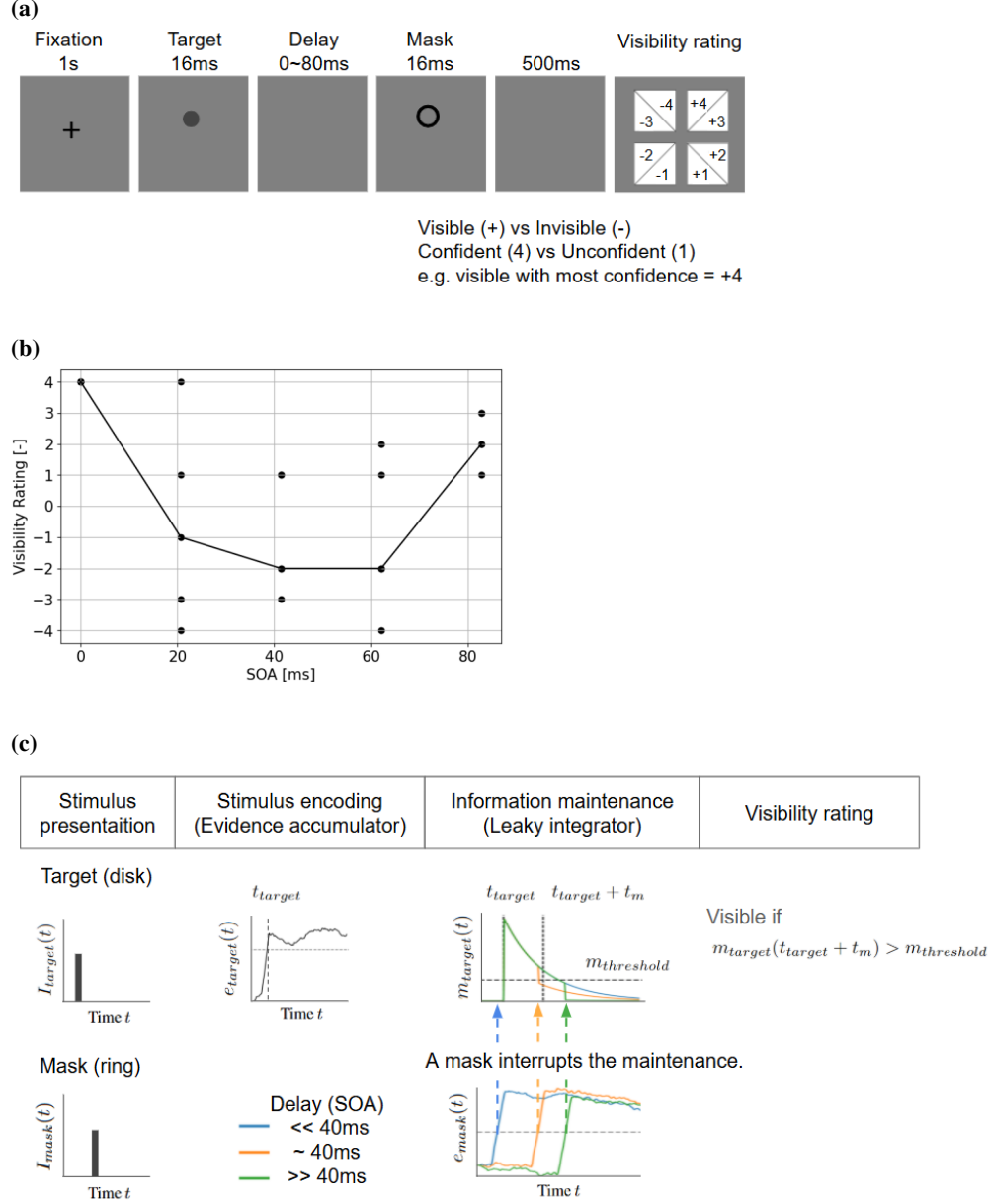


Figure 1: A metacontrast masking experiment and my model to replicate behavioural data. **(a)** A schematic of the experiment. A target grey disk was followed by a black ring mask with a random delay (stimulus onset asynchrony, SOA). Participants rated the disk's visibility at the end of each trial. **(b)** Visibility rating as a function of SOA (N=1). Dots show trial data and the line shows the median across trials. Five trials for each SOA. The disk became mostly invisible for SOA = ~40 ms. **(c)** A schematic of my model. An evidence accumulator for target stimulus encoding,  $e_{target}(t)$ , integrates the target stimulus,  $I_{target}(t)$ , over time. Another accumulator,  $e_{mask}(t)$ , for the mask stimulus,  $I_{mask}(t)$ . When the target evidence reaches a threshold at  $t_{target}$ , the target adds a positive impulse to a leaky integrator for information maintenance,  $m_{target}(t)$ . The mask adds a negative impulse to the leaky integrator, interrupting the information maintenance. The target becomes visible when the maintained information is above a threshold,  $m_{threshold}$ , after a fixed time,  $t_m$ . I checked whether the model replicated the behavioural data in Figure 1b. Note that the experiment required a binary decision with confidence rating while the model included only the binary decision. See the method section for details.

Metacontrast masking suggests that the brain needs to maintain external visual information before conscious perception. After a target disk presentation, the brain starts encoding the disk information and keeps it before generating conscious perception. A delayed mask can interrupt the information maintenance and make the disk invisible. When the delay is too short, the mask does not interrupt the information maintenance, possibly because the disk encoding is still incomplete. When the delay is too long, the mask does not make the disk invisible, possibly because the brain maintains the disk information long enough for conscious perception.

I modelled the maintenance of the target information and the interruption by the mask during metacontrast masking (Figure 1c). In the model, an evidence accumulator for target/mask stimulus encoding integrates the target/mask stimulus over time. The accumulation of the target evidence leads to a positive impulse input to a leaky integrator for information maintenance. On the other hand, the accumulation of the mask evidence leads to a negative impulse input to the leaky integrator, interrupting the information maintenance. When information is maintained for a sufficient duration, the target becomes visible.

In this report, I aimed to develop a phenomenological model that replicates the metacontrast masking effect. I considered the maintenance and interruption of stimulus information prior to conscious perception and modelled it as a leaky integrator with positive/negative impulse inputs. Simulated data, after parameter tuning, showed that  $\sim 40$  ms delays made the masking effect stronger than shorter/longer delays, qualitatively replicating the masking effect.

## 2 Method

### 2.1 Model

I developed a phenomenological model for visual processing during metacontrast masking experiments. The model included 1) target/mask stimulus presentation, 2) stimulus encoding, 3) information maintenance, and 4) visibility rating. (See Figure 1c).

I modelled the target stimulus,  $I_{target}(t)$ , and the mask stimulus,  $I_{mask}(t)$ , by using rectangular step functions. I considered the target stimulus from the onset time,  $t_{onset}$ , to the offset time,  $t_{offset}$ , with a constant intensity,  $A_{target}$ . I used the same function for the mask stimulus but with a delay,  $t_{delay}$ , and a different stimulus intensity,  $A_{mask}$ . I expressed the stimuli as follows:

$$I_{target}(t) = \begin{cases} A_{target}, & t_{onset} < t < t_{offset} \\ 0, & \text{otherwise} \end{cases}$$

$$I_{mask}(t) = \begin{cases} A_{mask}, & t_{onset} + t_{delay} < t < t_{offset} + t_{delay} \\ 0, & \text{otherwise} \end{cases}$$

I modelled stimulus encoding by using evidence accumulators. A time-dependent variable,  $e_{target}(t)$ , represents the progress of stimulus encoding (or accumulated evidence) and it integrates the target stimulus over time. I also included the mask encoding,  $e_{mask}$ . Here,  $e_{target}(t)$  and  $e_{mask}(t)$  are:

$$e_{target}(t) = \int_0^t I_{target}(t) + \eta_{target}(t) dt$$

$$e_{mask}(t) = \int_0^t I_{mask}(t) + \eta_{mask}(t) dt$$

, where  $\eta$  is zero-mean Gaussian noise with different variance values for the target and mask.

I modelled the maintenance of encoded target information by using a leaky integrator. A variable,  $m_{target}(t)$ , represents the maintained target information and follows a first-order differential equation. It receives a positive impulse input,  $i_{target}(t)$ , on the completion of the target encoding. It also receives a negative impulse input,  $i_{mask}(t)$ , on the completion of the mask encoding but only if the target encoding completes prior to the completion of the mask encoding. I used  $i_{target}(t)$  and  $i_{mask}(t)$  to express the dynamics of  $m_{target}(t)$ :

$$\tau_{target} \frac{dm_{target}(t)}{dt} = m_{target}(t) + i_{target}(t) + i_{mask}(t)$$

$$i_{target}(t) = \begin{cases} B_{target}, & t = t_{target} \\ 0, & \text{otherwise} \end{cases}$$

$$i_{mask}(t) = \begin{cases} -B_{mask}, & t = t_{mask} \text{ and } t_{target} < t_{mask} \\ 0, & \text{otherwise} \end{cases}$$

, where  $\tau_{target}$  is a time constant.  $t_{target}$  is the time when the evidence,  $e_{target}(t)$ , reaches a threshold,  $e_{target,threshold}$ , for the first time, corresponding to the completion time of the target encoding (and the same for the mask).  $B$  is the amplitude of impulse inputs.

Finally, the target stimulus becomes visible when the maintained information,  $m_{target}(t)$ , is above a threshold,  $m_{threshold}$ , after a fixed time period,  $t_m$ . A binary variable,  $v$ , represents the target visibility and can be expressed as follows:

$$v = \begin{cases} 1, & m_{target}(t = t_{target} + t_m) > m_{threshold} \\ 0, & \text{otherwise} \end{cases}$$

## 2.2 Simulation

I evaluated the model by assessing whether simulated behavioural data qualitatively matched the experimental data in Figure 1b. After parameter tuning, I run a simulation to obtain the target visibility,  $v$ , from 100 trials for each condition and calculated the proportion of trials where the stimulus was visible (i.e.  $v = 1$ ). I checked whether the proportion as a function of SOA showed a U-shaped curve.

I adjusted some parameters to match experimental conditions and fine-tuned the others to replicate the behavioural data (Table 1). Following the experimental setup, I set the stimulus presentation time to 16 ms and considered six SOAs ranging from 0 ms to 80 ms. Given the intensity difference between the grey disk (target) and the black ring (mask), I assigned a stronger stimulus intensity to the mask. I fine-tuned the remaining parameters to replicate behavioural data.

Table 1: Parameter values. See the method section for the explanation of parameters.

Target stimulus	$A_{target}$ [-]	0.5
	$t_{onset}$ [ms]	16
	$t_{offset}$ [ms]	32
Mask stimulus	$A_{mask}$ [-]	1
	$t_{delay}$ (SOA) [ms]	0, 16, 32, 48, 64, 80
Target encoding	Variance of $\eta_{target}$ [-]	0.1
	$e_{target,threshold}$ [-]	7
Mask encoding	Variance of $\eta_{mask}$ [-]	0.15
	$e_{mask,threshold}$ [-]	7
Information maintenance	$\tau_{target}$ [ms]	50
	$B_{target}$ [-]	1
	$B_{mask}$ [-]	0.2
Visibility rating	$m_{threshold}$ [-]	0.005
	$t_m$ [ms]	50

## 3 Result

I run a simulation and obtained simulated visibility responses from the model. Overall, the simulated data showed a U-shaped curve of masking effect (Figure 2). In the simulation, the target stimulus was invisible in most trials for SOA =  $\sim 40$  ms. Unlike the experimental data, the target stimulus became visible in most trials for SOA =  $\sim 20$  and 60 ms.

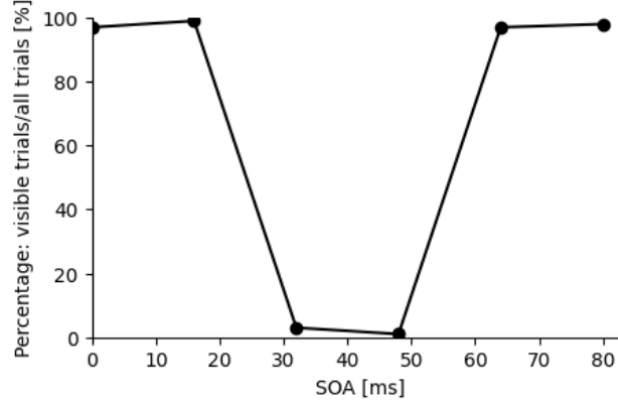


Figure 2: Simulated visibility responses. The y-axis shows the proportion of trials in which the stimulus becomes visible for each SOA.

## 4 Discussion

In this project, I developed a phenomenological model of the metacontrast masking effect and evaluated the model through simulation. I assumed that a mask stimulus made a target stimulus invisible by interrupting the maintenance of the target stimulus information. I modelled 1) the information maintenance as a leaky integrator and 2) the interruption by the mask stimulus as a negative impulse input to the leaky integrator. After parameter tuning, simulated data showed a strong masking effect for  $\text{SOA} = \sim 40$  ms.

The simulated data did not fully align with the experimental data. Specifically, the masking effect appeared binary in the simulated data. The data showed a strong masking effect for  $\text{SOA} = \sim 40$  ms, but not at all for the other SOAs (Figure 2). Further model refinements, such as incorporating noise into the information maintenance, might resolve the discrepancy between the simulated and experimental data.

A non-binary approach to behavioural responses may be appropriate for modeling conscious perception. The current model assumed a binary decision (visible or invisible) and does not account for confidence ratings of visibility. However, several studies argue that graded response scales, such as a four-point scale, better characterise conscious perception [Ramsøy and Overgaard, 2004, Sandberg et al., 2010]. There is still an ongoing debate between the binary and graded views of conscious perception [Kouider et al., 2010, Windey and Cleeremans, 2015].

Model modifications are necessary to prevent negative values of the maintenance variable,  $m_{\text{target}}(t)$ . The variable represents maintained encoded information and becomes uninterpretable when negative. In the current model, the variable can take negative values when the leaky integrator receives a delayed negative impulse input from the mask,  $i_{\text{mask}}(t)$ , long after receiving a positive impulse input from the target,  $i_{\text{target}}(t)$ . The model needs to be further refined to avoid this behaviour.

## 5 Code Availability

Google Colab code is available from the following link: <https://colab.research.google.com/drive/1aU63R83bzqh6Iv08-C-GGfrQ-1dkz3e?usp=sharing>.

## 6 Demo experiment

A demo experiment is available from the following: [https://run.pavlovia.org/Yota/standard\\_metacontrast](https://run.pavlovia.org/Yota/standard_metacontrast). Another visual masking demo is available on Youtube: <https://youtu.be/Si1nTnZIGI0?feature=shared> [Schieber, 2017]

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