A statistical perspective to visual masking

Sevda Agaoglu a,c, Mehmet N. Agaoglu a,c, Bruno Breitmeyer b,c, Haluk Ogmen a,c,*

a Department of Electrical and Computer Engineering, University of Houston, N308 Engineering Building 1, Houston, TX 77204-4005, USA
b Department of Psychology, University of Houston, Houston, TX 77204-5022, USA
c Center for Neuro-Engineering and Cognitive Science, University of Houston, Houston, TX 77204-4005, USA

A R T I C L E   I N F O

Article info

Article history:
Received 17 November 2014
Received in revised form 9 July 2015
Accepted 14 July 2015
Available online xxxx

Keywords:
Visual masking
Paracontrast
Metacontract
Structure masking
Noise masking
Statistical mixture models

A B S T R A C T

A stimulus (mask) reduces the visibility of another stimulus (target) when they are presented in close spatio-temporal vicinity of each other, a phenomenon called visual masking. Visual masking has been extensively studied to understand dynamics of information processing in the visual system. In this study, we adopted a statistical point of view, rather than a mechanistic one, to investigate how mask-related activities might influence target-related ones within the context of visual masking. We modeled the distribution of response errors of human observers in three different visual masking experiments, namely para-/meta-contrast masking, pattern masking by noise, and pattern masking by structure. We adopted statistical models, which have been used previously in studies of visual short-term memory, to capture response characteristics of observers under masking conditions. We tested the following scenarios: (i) mask activity may reduce a target's signal-to-noise ratio (SNR) without interfering with its encoding precision. (ii) Mask activity may “interfere” with the encoding of a target and cause decreased precision in observer's reports. (iii) Decreased performance due to masking may result from the confusion or “mis-binding” of a mask's features with those of the target, when they are similar as in the case of pattern masking by structure. Our results show that in all three types of masking, the reduction of a target's SNR (i) by suppressing or interrupting the signal of the target in para-/meta-contrast, (ii) by increasing noise in pattern masking by noise, and (iii) a combination of the two in pattern masking by structure.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

Visual masking is defined as the reduction in visibility of one stimulus (target) by another stimulus (mask) when the mask is presented in the spatio-temporal vicinity of the target (Bachmann, 1984; Breitmeyer & Ogmen, 2006). Visual masking has largely been investigated as a phenomenon reflecting the spatio-temporal dynamics of the visual system, and various models have been developed to explain its mechanistic bases (reviews: Bachmann, 1984; Breitmeyer & Ogmen, 2000; Breitmeyer & Ogmen, 2006; Enns & Di Lollo, 2000; Francis, 2000). Visual masking has also been used as an experimental tool, often to control the duration for which stimulus information remains available to the observer. After its offset, the stimulus registers first in a relatively large-capacity memory, known as iconic or sensory memory (Averbach & Sperling, 1961; Haber, 1983; Sperling, 1960). The contents of the iconic memory decay rapidly, within a few hundred milliseconds. A subset of the contents of iconic memory is transferred to a more durable store, visual short-term memory (VSTM). That VSTM is a different memory store than iconic memory has been supported by the findings that a visual mask can interfere with the contents of iconic memory but not with those of VSTM (e.g., Averbach & Coriell, 1961; Gegenfurtner & Sperling, 1993; Haber, 1983; Loftus, Duncan, & Gehrig, 1992; Schill & Zetzsche, 1995). Given this important criterion, visual masking has played a significant role in studies of visual memory.

The traditional view of VSTM is that, while it can store information for much longer times than iconic memory (few seconds vs. few hundred milliseconds), its capacity is severely limited. Most studies suggested a capacity limit of 4–5 items for VSTM (Cowan, 2001, 2005, 2010; Fukuda, Awh, & Vogel, 2010; Pasternak & Greenlee, 2005). Recent studies addressed whether VSTM stores...
its items in a fixed number of slots of equal resolution or uses a sharable resource that can be distributed among many items. Evidence for fixed slots came from studies of Zhang and Luck (2008) who used a statistical mixture model to decompose the distribution of errors into two components, a Gaussian distribution and a uniform distribution:

\[
PDF(e) = w_c \cdot G(\mu, \sigma) + (1 - w_c) \cdot U.
\]  

where PDF is the probability density function of errors, \(e\), in observers’ responses; \(G(\mu, \sigma)\) is a Gaussian distribution with mean \(\mu\), and standard deviation \(\sigma\); and \(U\) is a uniform distribution over the interval defining the errors. The Gaussian term represents reports of items in VSTM and the uniform distribution represents guesses. The parameter \(w_c\) models the proportion of responses from memory while \((1 - w_c)\) represents the proportion of guesses. The mean of the Gaussian represents the accuracy with which items are stored in VSTM and the inverse of the variance represents the precision with which items are stored. If VSTM is composed of a fixed number of discrete slots and the number of items to report is increased, the proportion of guesses should remain close to zero until all the slots are filled (i.e., the capacity of VSTM is reached) and increase thereafter. If the slots are of fixed precision, then the standard deviation should remain independent of the number of items. A second version of this model assumes that resources can be shared among the slots; in this case, the standard deviation should remain independent of the number of items when set-size exceeds the number of slots. While initial studies gave support for discrete, fixed-precision representations in VSTM (Fukuda et al., 2010; Zhang & Luck, 2008), more recent studies provided data favoring the shared-resource approach (e.g., Bays, Catalao, & Husain, 2009; van den Berg et al., 2012). Notwithstanding these differences, we note here the usefulness of this statistical modeling approach, which allows the separation of quantitative (\(w_c\): proportion of items stored in memory) and qualitative (\(1/\sigma\): precision with which items are stored) aspects of information encoding and storage.

Since a visual mask deteriorates the contents of iconic memory and hence affects what can be transferred into VSTM, our goal in this study was to characterize how masks affect the quality and quantity of information by using a similar modeling technique.

In particular, given the parameters of the statistical model in Eq. (1), we wanted to consider the following scenarios: (1) the mask may lead to a reduction in the weight of the Gaussian term (equivalently an increase in the weight of the Uniform term, since these two add to unity) without affecting the standard deviation or the mean of the Gaussian. This case may be interpreted as the mask reducing the signal-to-noise ratio (SNR) of the target signal without affecting the encoding quality of the target. Since signal and noise are intertwined in the SNR, a priori we cannot tell whether the reduction in SNR occurs via a reduction in signal strength, via an increase in noise strength, or via a combination of both. We will call this case the “SNR effect”. (2) The mask’s activity may “interfere” with the target’s encoding and cause a change in the mean and/or the standard deviation of the Gaussian term. We will call this case the “interference” effect. (3) Finally, by using an extension of the aforementioned model, we will also assess whether the decrease in performance due to masking results from the confusion or mis-binding of the mask’s features with those of the target, when the target and mask are similar as in the case of pattern masking by structure.

Since masking is not a unitary phenomenon (reviews: Bachmann 1984; Breitmeyer & Ogmen, 2006), we separately analyzed para-/meta-contrast masking, pattern masking by noise, and pattern masking by structure (see Fig. 1).

2. General methods

2.1. Participants

Five observers (three naive observers and the authors SA and MA) participated in the study. The age of the participants ranged from 26 to 39 years and all participants had normal or corrected-to-normal vision. The work was carried out in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki). Experiments followed a protocol approved by the University of Houston Committee for the Protection of Human Subjects. Each observer gave written voluntary informed consent before the experiments.

2.2. Apparatus

Visual stimuli were created using the ViSaGe card manufactured by Cambridge Research Systems. Stimuli were displayed on a 22-in. CRT monitor. Resolution was set to 800 × 600 and the refresh rate was 100 Hz. Observers were at a distance of 1 m from the screen. In order to help observers to keep a stable gaze, a fixation cross at the center of the screen and a head/chin rest were provided. Behavioral responses were recorded via a joystick. We devoted 100 trials to each stimulus onset asynchrony (SOA) separating the onset of the target from that of the mask, in order to obtain a satisfactory number of data points for statistical tests. The entire experiment required 15 sessions, with 5 separate sessions for each masking type. The order of the sessions for different masking types was randomized in order to minimize order effects. To assess baseline target visibility, twenty trials in which only the target was presented were interleaved in every session. Practice trials were run to familiarize the observers with the task and the settings of the experiments.

2.3. Stimuli

The target and the mask were presented at a 6-deg horizontal eccentricity in the right half of the display while the observers fixated at the center of the screen. Background luminance was 40 cd/m². The target was an oriented bar, 1 deg long and 0.1 deg wide (Fig. 1a). The luminance of the target differed for each type of masking and exact values will be specified in respective sections. The mask (Fig. 1b–d) was either a non-overlapping ring (para-/meta-contrast) or a random dot pattern (masking by noise) or 3 bars with the same dimensions as the target but varying in orientation (masking by structure).

Fig. 2 shows an example of the stimulus sequence. Each trial started with a fixation cross. The duration of the fixation cross was randomly chosen from the values between 0.5 s and 1 s. For positive SOA values, the target was shown first, followed by a blank interval determined by the SOA value. For negative SOA values, the order was reversed. Observers were asked to give their responses by adjusting via a joystick the orientation of a bar shown 1500 ms after the offset of the stimulus at the center of the screen. No feedback was provided to the subjects. The initial orientation of the response bar was randomly chosen among the values ranging from 0 to 179 deg. The resolution of the adjustment via joystick was 1 deg of orientation.

1 Performance depends both on the strength of the target signal, captured by the weight of the Gaussian, and the encoding quality of the target signal, captured by the mean and the standard deviation of the Gaussian. When we refer to signal-to-noise ratio, we are referring to the relative weights of the target Gaussian and the uniform distributions. While one may also consider the accuracy and precision limits (i.e. the mean and the standard deviation, respectively, of the Gaussian) to stem also from noise processes, our use of noise in this manuscript refers exclusively to that underlying the relative weights of the target Gaussian and the uniform distribution.
Para-/meta-contrast masking and pattern masking by structure typically generate Type-B masking functions (maximum masking occurs at a positive SOA value) whereas pattern masking by noise generates Type-A functions (maximum masking occurs at SOA = 0) (Breitmeyer & Ogmen, 2006). Since we focused on different parts of masking functions for Type-A and Type-B, we employed different SOA values for different mask types. The durations of the target and the mask were 10 ms.

2.4. Analysis

To obtain masking functions, we transformed each observer’s orientation settings at each SOA for the three types of masks used here, by first computing response errors. Error values were calculated as the difference between the actual and the reported angles. Error values ranged from –90 to 90 deg. Transformed performance (Ögmen, Ekiz, Huynh, Bedell, & Tripathy, 2013) was then calculated as:

\[
\text{Transformed Performance} = 1 - \frac{|\text{Error angle}|}{90}
\]

When the observer produces no errors, error angle will be zero, resulting in a Transformed Performance value of 1. When the observer purely guesses, the average of the absolute value of error angles will be 45 deg. The corresponding Transformed Performance will be 0.5. Hence, transformed performance is a linear transform that converts errors to a probability-like measure such that transformed performance values of 0.5 and 1 correspond to chance and perfect performance, respectively.

2.5. Statistical models

We adopted statistical models that have been used previously in modeling VSTM (Bays et al., 2009; Zhang & Luck, 2008). In pattern masking by noise and para-/meta-contrast masking paradigms, we analyzed two different models to explain the masking effect. The first model (Gaussian) suggests that the masking effect is caused by the “interference” of the mask signal with the target signal in such a way that the encoding precision and/or accuracy for the target signal is hampered. Decreased stimulus encoding precision is reflected by the increased variability of behavioral responses. A Gaussian distribution (Fig. 3a) is used to model this effect (the Gaussian model will be referred to as the G model). The mean of the Gaussian distribution converts to a measure of the accuracy of the system; i.e., the closer the mean to 0 the more accurate the system. The reciprocal of the standard deviation of the Gaussian distribution reflects the encoding precision of the system. In the second model, Gaussian + Uniform (the GU model), an increased guess rate caused by a drop in the target’s SNR is also considered. The increased guess rate is modeled by the weight of the uniform distribution as shown in Fig. 3b. The GU model is a weighted sum of Gaussian and Uniform distributions (Eq. (3)).
PDF(ε) = \(e_0 \cdot G(\mu, \sigma) + (1 - e_0) \cdot U\).  

In pattern masking by structure, since the mask elements share structural properties of the target, there is a possibility to report one of the mask elements, e.g., the one that has the closest angle to the target angle and the closest location to the target location, instead of the target stimulus. In this case, the masking effect would be caused by incorrect identity binding and it is modeled by an extra Gaussian distribution shown in Fig. 3c. If the source of this extra Gaussian component is the mask element which has the closest angle to the target angle, then the model is “Gaussian + Uniform + Closest Angle”, and it will be referred to as the GUCA model. If misbinding is caused by the mask element which has the closest angle to the target angle, then the model is “Gaussian + Uniform + Nearest Neighbor”, and it will be referred to as the GUNN model. In this case, the PDF is a weighted sum of Gaussian and non-target Gaussian distributions and the Uniform distribution (Eq. (4)) (Bays et al., 2009). We call this model “the Misbinding model”.

\[
PDF(\epsilon) = w_T G(\mu_T, \sigma_T) + w_{NT} G(\mu_{NT}, \sigma_{NT}) 
+ (1 - w_T - w_{NT})U(-\pi/2, \pi/2) 
\]

where subscripts T and NT denote target and non-target parameters, respectively. Note that models come from an embedded family, i.e., two or more PDFs are embedded into a family of PDFs that are indexed by one or more parameters (Kay, 2005). Given the different number of parameters in each model, an adjustment for the number of parameters is needed for comparing model performances. For instance, the Misbinding model contains the components of the GU model, and the same relationship is valid for the GU and G models, too. These relationships allowed us to identify potential contributions of different mechanisms; if adding a new component to the model enhances model performance (how well the model explains the experimental data), then it would imply presence of a mechanism modeled by this new component.

2.5.1. Model fitting and model comparison

We used two different techniques to determine model parameters and to compare different models. In the first technique, we used the Least-Mean-Squares (LMS) approach to find the best fitting parameters and the adjusted-\(R^2\) criterion to select the model that explains the data best. The results of these analyses are presented in Appendix A. As a second approach, we used the Bayesian Model Comparison (BMC) technique (MacKay, 2003; Wasserman, 2000). We present the BMC technique and its results in the main text of the manuscript. Overall, the two techniques produced very similar results, thereby indicating that both our parameter determination and our model selection process were robust.

Each model \(m\) produces a predicted error distribution \(p(\epsilon|m, \theta)\), where \(\epsilon\) is a vector of observed response errors, and \(\theta\) is a vector of model parameters. For each model, we calculated the likelihood of finding observed response errors, averaged over free parameters:

\[
L(m_i) = \int p(\epsilon|m_i, \theta)p(\theta|m_i)d\theta 
= \left(\prod_{j=1}^{N} p(\epsilon|m_i, \theta)\right)p(\theta|m_i)d\theta, 
\]

where \(N\) represents the number of trials and \(i\) represents the error in the ith trial. It is convenient to take the logarithm of Eq. (5) in order to compute it numerically. Eq. (5) can be rewritten as

\[
\ln L(m_i) = \ln L_{\max}(m_i) + \ln \int \left[ \exp(\ln L(m_i|\theta) - \ln L_{\max}(m_i))p(\theta|m_i)d\theta \right], 
\]

where \(\ln L(m_i|\theta) = \sum_{t=1}^{T} \ln p(\epsilon_t|m_i, \theta)\) and \(L_{\max}(m_i) = \max(L(m_i|\theta))\). Parameters corresponding to \(L_{\max}(m_i)\) can be regarded as the Maximum Likelihood Estimation (MLE) of the model parameters for model \(m_i\). Subtracting \(L_{\max}(m_i)\) ensures that the exponential in the integrand is of order 1 and thereby, avoids numerical problems (Ester, Zilber, & Serences, 2015; MacKay, 2003; van den Berg, Shin, Chou, George, & Ma, 2012). Since we do not have an a priori reason to do otherwise, we used a uniform distribution over a plausible range of parameters for the parameter prior distributions (see Table 1). For G and GU models, the priors were a one- and two-dimensional uniform distributions, respectively:

\[
p(\theta|m_i) = \prod_{t=1}^{k} U(\theta_{t_{\min}}, \theta_{t_{max}}), 
\]

where \(U(ab)\) represents a uniform distribution over the interval \([a, b]\), \(k\) represents the number of free parameters in the model, \(m_i\) and \(\theta_{t_{min}}\) and \(\theta_{t_{max}}\) represent the minimum and maximum boundaries for the rth free parameter. For GUCA and GUNN models, both of which have four free parameters, the probabilities over parameter space were again uniform distributions; but the prior was not simply a hypercube with \(n = 4\), (i.e., a product of four independent uniform distributions), since not all model parameters are independent for these models. To be more specific, the sum of \(w_{\text{target}}\) and \(w_{\text{non-target}}\) cannot exceed 1. If the range for \(w_{\text{target}}\) is \([0, 1]\), the corresponding range for \(w_{\text{non-target}}\) can only be \([0, 1-w_{\text{target}}]\). In other words, the support of the probability function is the triangular region consisting of the non-negative space with \(w_{\text{target}} + w_{\text{non-target}} \leq 1\). Since all other parameters are independent, the joint prior for GUCA and GUNN models can be expressed as a product of three independent uniform distributions and a triangular distribution. For the parameter \(\mu_T\), the mean of the target Gaussian, we chose \(\mu_T = 0\), corresponding to a Dirac delta function as prior. This was motivated by the following: In visual masking, there is no a priori reason to expect a significant bias for the mean of the Gaussian (in contrast, in visual crowding for instance, such systematic trends can be expected (see for example: Ester et al., 2015; van den Berg, Johnson, Martinez Anton, Scheipers, & Cornelissen, 2012)). Indeed, in our approach using the LMS + adjusted \(R^2\) method, we found that the mean of the Gaussian is not significantly different from zero.

![Fig. 3](image-url) Statistical models tested in this study. (a) Gaussian, (b) Gaussian + Uniform and (c) Gaussian + Uniform + Misbinding Terms.
Therefore, in the following analyses, the target Gaussians were centered on target orientations (i.e., zero mean in error space), which decreased the number of free parameters in all models.

Considering these priors, Eq. (6) becomes

$$\ln L(m) = \ln L_{\text{max}}(m) - \sum_{j} \ln(R_j)$$

$$+ \ln \left[ \exp(\ln L(m|h) - \ln L_{\text{max}}(m))dh \right],$$

where $R_j$ represents the size of the range for the $j$th free parameter. We approximated the integral by a Riemann sum with at least 50 bins in each parameter dimension (we also repeated the analysis for $G$ and $GU$ models with 500 bins in each parameter dimension and verified that the results with 50 bins are sufficiently robust). We refer to the performance metric given in Eq. (8) as BMC. The difference between BMC from two different models is equivalent to the log of their likelihood ratios.

### 2.5.2. Analysis of model parameters

After determining the best model in explaining the statistics of observers' response errors, we sought to find how different model parameters change as a function of SOA. The reasoning behind this analysis was to determine which one of the scenarios listed in the Introduction section best accounts for the visual masking

### Table 1

Range of parameters used for BMC. Note that in a separate analysis for para/meta-contrast masking and pattern masking by noise, we used step sizes of 0.1 for the standard deviation of the Gaussian, and 0.002 for the weight of the Uniform but the winning model and the pattern of changes in model parameters were not affected by this change.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Upper bound</th>
<th>Lower bound</th>
<th>Step size</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_T$</td>
<td>50</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>$W_U$</td>
<td>1000</td>
<td>0</td>
<td>0.02</td>
</tr>
<tr>
<td>$W_{NT}$</td>
<td>1000</td>
<td>0</td>
<td>0.02</td>
</tr>
<tr>
<td>$\sigma_{NT}$</td>
<td>50</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

$\sigma_T$, standard deviation of the target Gaussian.

$W_U$, weight of the Uniform.

$W_{NT}$, weight of the non-target Gaussian.

$\sigma_{NT}$, standard deviation of the non-target Gaussian.

(see Appendix A)
phenomenon. We examined the model parameters that yielded $L_{\text{max}}$ to see how they vary as a function of SOA and compared the results to the masking functions in order to assess whether they correlate well with masking. We report traditional ANOVA results as well as Bayes factors for this analysis. Bayes factor analyses were done in the programming language R using the “BayesFactor” package developed by Rouder et al. (available for download at bayesfactorpcl.r-forge.r-project.org, see also for reference Rouder, Morey, Speckman, & Province, 2012). We also quantified the correlation between the model parameters and the masking strengths by calculating Pearson $R$ coefficients. Masking strength is calculated as the difference between baseline performance, when the target is presented alone, and the performance when the target and mask are presented together. A strong correlation between a parameter and the masking strength would suggest a critical role for this parameter for explaining how masking occurs.

3. Experiments

3.1. Para-metacontrast masking

3.1.1. Methods

In para-metacontrast masking, we tested two statistical models, namely G and GU, as mentioned before. The G model states that the masking effect occurs due to an “interference” by the mask signal on the target signal so as to impair stimulus-encoding precision for the target. This prediction will be reflected as an increased variability in an observer’s responses. On the other hand, the GU model takes an additional mechanism into account, which amounts to “a reduction of target SNR by the mask signal. According to this model, a decrease in target SNR will lead to an increase in the guess rate (modeled by an increasing weight of the uniform distribution and a decreasing weight for the Gaussian distribution; note that these two weights add to unity).

General methods and procedures were followed. Specific to para-metacontrast experiment, the target luminance was either 25 cd/m$^2$ or 30 cd/m$^2$ depending on the observer. The value was chosen to yield a considerable drop in performance due to masking (at least 15% transformed performance drop from baseline). In para-metacontrast masking, SOA values were $-100$, $-50$, $-10$, 0, 20, 40, 50, 60, 80, 110, 150, 200 ms. The mask was a non-overlapping ring having 1.1 deg inner and 1.4 deg outer diameters, respectively, as shown in Figure 1b. The luminance of the mask was 5 cd/m$^2$.

3.1.2. Results and discussion

Mean error distributions for several SOA values are given in Figure 4. Distribution of response errors follows a Gaussian-like distribution at SOA values where visual masking is weak or absent (i.e., SOA < 0 ms or SOA > 60 ms). However, at SOA values where there is strong masking (e.g., SOA = 40 ms), the tails of the error distribution increases, indicating the involvement of a uniform component.

In order to quantitatively assess these qualitative observations, we fitted observers’ response errors with the statistical models described before. We used Bayesian Model Comparison (BMC) to compare model performances. This method returns the average log-likelihood of each model over the selected parameter space (see Table 1) given the observed response errors. We then averaged the log-likelihoods across all SOAs for each observer and subtracted the average likelihood of the G model from that of GU model (see Table B.1 in Appendix B for individual BMC differences and corresponding Bayes factors). In this notation, a difference of $D$ means that the observed responses are, on average, $e^D$ times more likely under the GU model.

Pooled across SOAs, the GU model outperformed the G model for all observers in para/meta-contrast masking experiment. Averaged across observers, log-likelihoods (i.e., BMCs) were $10.6 \pm 3.9$ units larger for the GU model. This corresponds to $40,000$-to-$1$ odds favoring the GU model. According to Jeffrey’s scale of interpretation (Jeffreys, 1998), this corresponds to a “decisive evidence” for the GU model and indicates that in the present study “guessing” was an essential part of para/meta-contrast masking. Next, we extracted the model parameters of the GU model that resulted

![Fig. 5. (A) Para/meta-contrast masking functions for each observer. Transformed performances are plotted as a function of SOA. The dotted line represents the average baseline performance. (B) Mean masking strengths as a function of SOA. Model parameters are presented here for only the winning GU model. (C) The standard deviation of the Gaussian in the GU model as function of SOA. (D) The guess rate, i.e., the weight of the Uniform in the GU model as a function of SOA. (E) Correlation of model parameters with masking strengths. Error bars in all panels except in A represent SEM across observers ($n = 5$), whereas in A, they represent SEM across trials ($n = 100$).](image-url)
in the maximum average log-likelihood for each observer. We sought to find correlations between masking functions (more specifically, masking strengths, defined as the differences between performances with and without the masks). Fig. 5 shows para-/meta-contrast masking functions (Fig. 5A), corresponding average masking strengths (Fig. 5B), average model parameters for the best fitting (GU) model (Fig. 5C and D), and the correlations of each model parameter with masking strengths.

Masking functions along with the average baseline performance of all observers are shown in Fig. 5A. The horizontal axis shows the SOA between target and mask stimuli, whereas the vertical axis represents the transformed performance. As expected, performance shows typical Type-B U-shaped patterns with dips occurring at positive SOA values. In other words, the masking strength, defined as the drop in performance from baseline, reaches its maximum at a positive SOA (Fig. 5B).

The standard deviation of the Gaussian in the GU model increases as SOA values approach 50 ms (where masking is most effective) and then decreases to a plateau (Fig. 5C). A one-way ANOVA confirms a significant effect of SOA on standard deviation ($F(11,44) = 5.259, p < 0.001$; Bayes factor: 618 ± 0.4%). The weight of the uniform distribution also shows a significant change with SOA ($F(11,44) = 14.680, p < 0.0001$; Bayes factor: 1.4E+9 ± 1.6%).

Visual comparison of model coefficients (Fig. 5C and D) with masking strengths (Fig. 5B) reveals that the standard deviation of the Gaussian term and the weight of the Uniform term do correlate with masking strengths, the latter having a stronger correlation than the former. Pearson’s $R$ coefficients confirm these qualitative observations. We found that both the standard deviation of Gaussian and the weight of Uniform in the GU model strongly correlate with the masking strength (one sample $t$-test results show $p < 0.0001$ for both parameters).

Stronger correlation between the weight of the Uniform distribution and the masking strength indicates that, as the masking strength increases, observers tend to guess more, suggesting that the target SNR is reduced by the mask activity in the visual system. Our results also suggest that the “interference” of the mask signal with the target signal, which is manifested by the increased standard deviation of the Gaussian term in the model and also by the significant correlation with the masking strength, is also present.

3.2. Pattern masking by noise

3.2.1. Methods

Similar to para-/meta-contrast masking, we tested two statistical models namely G and GU as mentioned before. The general
methods and procedures were identical to para-/meta-contrast masking experiments. Specific to the pattern masking by noise experiment, the target luminance was 25 cd/m² for all observers. In pattern masking by noise, SOA values were −100, −70, −50, −30, −10, 0, 10, 30, 50, 70, 100, 150 ms. The noise mask, as shown in Fig. 1c, was composed of 70 randomly located disks (diameters ranging from 0.2 deg to 0.3 deg), which could overlap and were confined to 2 × 2 deg area. We made sure that the noise masks did not have bias in any particular orientation, by obtaining 2D Fourier transforms of 100 randomly generated masks. Visual inspection of the magnitude and phase responses revealed no significant peaks or dips, hence no biases in any orientation. The luminance of the disks composing the mask was 5 cd/m².

3.1.3. Results and discussion

Mean error distributions for several SOA values are given in Fig. 6. Distribution of response errors follows a Gaussian-like distribution at SOA values where visual masking is weak or absent (i.e., SOA < −30 ms or SOA > 30 ms). At SOA values where masking is strongest (e.g., SOA = 0 ms), performance is near chance and the distribution of errors is uniform.

The GU model outperformed the G model for all observers in noise masking (see Table B.1 in Appendix B for individual BMC differences and corresponding Bayes factors). Averaged across observers, log-likelihoods (i.e., BMCs) were 6.4 ± 3.5 units larger for the GU model. This corresponds to ~600-to-1 odds favoring the GU model. According to Jeffrey’s scale of interpretation (Jeffreys, 1998), this corresponds to “decisive evidence” for the GU model and indicates that “guessing” is an essential part of pattern masking by noise. Individual masking functions along with the average baseline performance of all observers are shown in Fig. 7. The horizontal axis again represents the SOA between target and mask stimuli whereas the vertical axis shows the transformed performance. As expected (Breitmeyer & Ogmen, 2006), performance shows a Type-A masking function with the strongest masking occurring at 0 ms SOA (Fig. 7B).

Fig. 7C and D shows model parameters against SOA values. Standard deviations of the Gaussian in the GU model appears to change as a function of SOA (Fig. 7B and C); however, a one-way ANOVA of standard deviations yielded no significant effect of SOA (F(11,44) = 1.775, p = 0.088; Bayes factor: 1.2 ± 1.1%). Consistently, we found no significant correlation (average R = 0.220, one sample t-test: p = 0.294) between standard deviation and masking strength. In contrast, as with para-/meta-contrast masking, guess rate strongly correlates with the masking strength (Fig. 7B–D): The stronger the masking effect, the higher the guess rate, reflected in the weight of the uniform component in the GU model. This SOA-dependent modulation of “guessing”, i.e., the weight of the Uniform, is highly significant (F(11,44) = 59.130, p < 0.0001; Bayes Factor: 11.5E+20 ± 2.7%). Correlation of the weights with the masking strength was also highly significant for all observers (p < 0.0001).

In summary, these results suggest that pattern masking by noise exerts its effect mainly by reducing the SNR of the target. Since the mask consists of noise, it is reasonable to assume that SNR is reduced by increasing the noise that co-exists with the target signal.

3.3. Pattern masking by structure

3.3.1. Methods

In pattern masking by structure, the mask elements share structural properties of the target. Therefore, the possibility of observers reporting one of the mask elements instead of the target stimulus cannot be discounted. For instance, the mask element that has the closest angle to the target angle, or the one that has the closest location to the target location may be reported by mistake. In this case, the masking effect, which is caused by incorrect feature binding, i.e. misattribution of orientation of a mask element to the target is modeled by an extra Gaussian distribution. In addition to the G and GU models, we tested two different misbinding models, namely Closest Angle (GUCA) and Nearest Neighbor (GNN) for pattern masking by structure. These models have a separate Gaussian term in addition to the Gaussian and Uniform components. In the GUCA model, the mean of the second Gaussian term is determined by the mask element that has the closest angle.
to the target orientation whereas it is determined by the mask element that is the nearest neighbor of the target bar in the GUNN model.

The general methods and procedures were identical to previous experiments. Specific to the current experiment, the target luminance was 5 cd/m² for all observers. In this experiment, SOA values were -100, -50, -10, 0, 20, 40, 50, 60, 80, 110, 150, 200 ms. The mask shown in Fig. 1d, was composed of 3 randomly oriented bars with the same size as the target. Mask elements were randomly located inside a 2 × 2 deg virtual rectangle. The mask luminance was either 10 cd/m² or 20 cd/m² depending on the observer. The value was chosen to yield a considerable drop in performance due to masking (at least 25% transformed performance drop from baseline).

3.1.4. Results and discussion

Mean error distributions in pattern masking by structure for several SOA values are given in Fig. 8. The response errors follows a Gaussian-like distribution with varying standard deviations at all SOA values. At SOA values where masking is strongest (e.g., 10 ms < SOA < 50 ms), the increased tails of the distribution suggest the involvement of a uniform component.

Fig. 8. Mean error distributions and GU model fits in pattern masking by structure. Each panel corresponds to a different SOA value. Best fitting GU models are shown with solid blue lines. Model fits are generated by using the model parameters averaged across observers. Error bars represent SEM across observers (n = 5).

Fig. 9A plots individual masking curves and average baseline performance against SOAs. Across the entire SOA range, performance shows Type-B U-shaped patterns with dips occurring at positive SOAs. However, as expected (Breitmeyer & Ogmen, 2006), at positive SOAs (backward masking) the functions tended to approximate a J-shape more than a U-shape (compare results of Fig. 9A to those of Fig. 5A).

Fig. 10 shows individual as well as average BMC differences for all model types (see Table B.I in Appendix B for individual BMC differences and corresponding Bayes factors). For all observers, the GUCA and GUNN models performed much better than the G model. However, the GU model, once again, outperformed all other model types. The average BMC difference between the GU and G models was 10.2 ± 3.1, which corresponds to ~27,000-to-1 odds decisively favoring the GU model. The following discussion on model parameters focuses on this model.

The standard deviation of the Gaussian term and the weight of the uniform distribution in the GU model are plotted against SOA in Fig. 9C and D. The effect of SOA on standard deviations failed to reach significance (F(11,44) = 1.515, p = 0.160; Bayes factor: 0.7 ± 0.5%). The weight of the uniform distribution changed significantly with SOA (F(11,44) = 18.020, p < 0.0001; Bayes factor: 12.4E
We found a weak but significant correlation between the standard deviation of the Gaussian and the masking strength ($R = 0.322 \pm 0.113$, one-sample $t$-test: $p = 0.003$). On the other hand, we found a strong correlation between the weight of the uniform distribution and the masking strength ($R = 0.870 \pm 0.033$, one-sample $t$-test: $p < 0.0001$). Hence, it should be noted that a major factor in producing a masking effect is a reduction in SNR because the weight of the Uniform term strictly follows the masking strength whereas the standard deviation of the Gaussian does not. Therefore, these findings suggest that pattern masking by structure also occurs, from a statistical point of view, primarily due to the reduction of target SNR and only partly, if at all, to the interference of the target signal with the mask related activity.

4. General discussion

In this study, we adopted a statistical point of view to investigate interactions between target- and mask-related activities within the context of visual masking. We modeled the distribution of the response errors of human observers in three different visual masking experiments, namely para-/meta-contrast masking, pattern masking by noise, and pattern masking by structure. Table 2 summarizes the results. In all masking types, the GU model was the winning model, showing that a single statistical model was able to capture the response characteristics of the observers in three different masking types. We now discuss how one can interpret the parameters of the statistical model in terms of underlying mechanisms of masking.

In our LMS + adjusted $R^2$ based analysis, we did not find any systematic change in the means of the Gaussian term in the model.
indicating no bias for any target orientation in any of the masking types. Hence, the mask did not interfere with the accuracy of target encoding. Whereas bias was not found in the masking experiments here, it is worth discussing the implications of finding a bias as we would expect biases in two masking related phenomena. First, in feature attribution or feature inheritance, features of the target are transposed to the mask (Agaoglu, Herzog, & Ögmen, 2012; Enns, 2002; Herzog & Koch, 2001; Hofer, Waldner, & Groner, 1989; Ögmen, Otto, & Herzog, 2006; Otto, Ögmen, & Herzog, 2006, 2008; Stewart & Purcell, 1970; Werner, 1935; Wilson & Johnson, 1985). Hence, if observers were to report features of the mask, one would expect systematic biases that are congruent with the features of the target. Second, in masked-priming studies (Ansorge, Klotz, & Neumann, 1998; Klotz & Neumann, 1999; Schmidt, 2002; Vorberg, Mattler, Heinecke, Schmidt, & Schwarzbach, 2003), observers are asked to make speeded responses to the mask (rather than the target). The congruence of a target's features with those of the mask produces faster responses. Hence, again one may expect target-congruent biases if observers were to report features of the mask. Biases would be expected as well if this modeling were to be applied to other visual phenomena, such as visual after-effects and crowding (Ester et al., 2015; van den Berg, Johnson et al., 2012). However, the finding that the target orientations were reported without any bias in the present study was an expected consequence of the way we designed our mask stimuli, in that they did not have any systematic orientation bias.

When masking is very strong, as we observed here in the case of SOA = 0 ms in structure masking by noise, observers guess and the finding that the error distribution is uniform becomes trivial. However, there is no a priori reason to expect that, when masking strength is reduced, a uniform distribution will play a role in explaining masking. In fact, due to the choice of stimulus parameters used in this study, observers are at chance only for SOA = 0 ms in pattern masking by noise, but not in para-/meta-contrast masking and pattern masking by structure. Therefore, the fundamental role identified for the uniform distribution in this study is supported by the analysis of all the data points that are above chance level. In all masking types studied here, an increase in the weight of the Uniform distribution (and equivalently a decrease in the weight of the Gaussian term) correlated most strongly with masking strengths (see Table 2). Since the changes in the weights of the Gaussian and Uniform terms are interpreted as changes in the target SNR, the masking effects mainly manifest themselves as a reduction of target SNR. While in the statistical model, decreases in signal strength and increases in noise are intertwined, we can speculate on the individual changes in signal strength and in noise based on the assumption that noise is most effective when it is integrated with the target signal. Accordingly, an increase in the noise component of SNR would be most effective at 0 ms SOA when target and mask temporal integration is maximal. Based on this assumption we suggest that:

1. In metacontrast, relatively weak masking occurs at 0 ms SOA and maximum masking occurs at positive SOA (U-shaped Type-B), implying that masking occurs mainly by the reduction of the signal in the SNR, with the mask interrupting or suppressing the strength of the target activity.
2. In pattern masking by noise, maximum masking occurs at 0 ms SOA (Type-A), implying that masking occurs mainly by an increase in the noise component of the SNR.
3. In pattern masking by structure, one obtains strong masking at 0 ms SOA and maximum masking at positive SOA (J-shaped Type-B), implying that masking occurs both by increases in noise and decreases in signal of the SNR.

Appendix A

Here we demonstrate the robustness of our results by employing another model fitting approach and model comparison metric. We fitted each model by using the LMS technique, which minimizes the squared sum of errors between the model prediction and the actual data. We, then, evaluated the performance of each model by using adjusted $R^2$ coefficients. Adjusted $R^2$ is a standard unbiased model selection criterion and takes the number of parameters and the number of samples into account so that models with varying number of parameters can be pitted against each other (Ebberler, 1975; review: Hocking, 1976). Calculation of adjusted $R^2$ in terms of coefficient of determination ($R^2$) is given in Eq. (A.1).

\[
\text{Adjusted } R^2 = 1 - \left(1 - R^2\right) \frac{n-1}{n-p-1},
\]

where $n$ is the sample size (100 trials per SOA) and $p$ is the number of parameters in the model.

Due to circular nature of the error values (−90°–90° degr), using a wrapped Gaussian (von Mises distribution) function is more appropriate than using a standard Gaussian function. However, when the standard deviation of the Gaussian is small, the difference between single and wrapped Gaussians is negligible (Shooner, Tripathy, Bedell, & Ögmen, 2010). The Probability density function of a wrapped Gaussian in the context of this study can be expressed as,

\[
f(\varepsilon, \mu, \sigma) = \frac{1}{\lambda} \sum_{l=-\infty}^{\infty} \exp\left(-\frac{(\varepsilon - \mu + k180)^2}{2\sigma^2}\right).
\]

where $\varepsilon$ is response error, $\mu$ and $\sigma$ are mean and standard deviation of a standard Gaussian, $k$ represents the number of wrappings, and $\gamma$ is a normalization factor. When $k = 0$, Eq. (A.2) becomes equivalent to a standard Gaussian. The operation described by Eq. (A.2) is nothing but adding shifted Gaussians centered on multiples of ±180° degr and normalizing such that area under the curve within ±90° degr error values summed to unity. We picked two different wrappings ($k = 0$: standard Gaussian and $k = 10$) to test if wrappings have any effect on adjusted $R^2$.

Given that the optimization algorithm can be trapped in a local minimum due to multi-dimensionality of the parameter space (2-, 3-, and 6-dimensional for the G, GU, and Misbinding models, respectively), we ran the model simulations 200 times for each number of wrappings with randomly chosen initial parameters. We picked the optimum parameters, which resulted in the largest adjusted $R^2$ coefficients, because the larger the adjusted $R^2$ coefficients are, the better the model performs.

After determining the best model based on adjusted $R^2$ metric, we quantified the correlation between the model parameters (mean and standard deviation of the Gaussian term, the weight of the Uniform component) and the masking strengths by calculating Pearson $R$ coefficients. A strong correlation between a parameter and the masking strength would suggest a critical role for this parameter for explaining how masking occurs.

A.1. Para-/meta-contrast masking

The GU model performs better than the G model according to adjusted $R^2$ values (Fig. A1), consistent with model selection by using BMC. The mean of the Gaussian, which represents bias in orientation judgments, if any, shows no systematic pattern of change as a function of SOA as revealed by a one-way ANOVA ($F(11,44) = 0.914, p = 0.536, \eta^2_p = 0.186$) (Fig. A2A). However, the standard deviation of the Gaussian in the GU model increases as SOA values approach 50 ms (where masking is most effective) and then...
decreases to a plateau (Fig. A2B). A one-way ANOVA confirms a significant effect of SOA on standard deviation ($F(11,44) = 4.056, p < 0.001, \eta^2_p = 0.504$). Last but not the least, the weight of the uniform distribution shows significant change with SOA: $F(11,44) = 13.601, p < 0.001, \eta^2_p = 0.773$ (Fig. A2C). Visual comparison of model coefficients (Fig. A2A–C) with masking strengths (Fig. A2D) reveals that the mean of the Gaussian term does not correlate with masking strength but the standard deviation of the Gaussian term and the weight of the Uniform term do, the latter having stronger correlation than the former. Pearson’s $R$ coefficients confirm these qualitative observations. Fig. A2E depicts Pearson’s $R$ coefficients averaged across observers for each model parameter. $R$ coefficients for mean did not reach significance ($t(4) = 0.310, p = 0.772$) whereas those for standard deviation and weight were highly significant (standard deviation: $t(4) = 10.150, p < 0.001$; weight: $t(4) = 73.722, p < 0.00001$). Furthermore, the weight of the Uniform was more strongly correlated with the masking strength than the standard deviation of the Gaussian (paired $t$-test: $t(4) = 6.104, p = 0.004$).

A.2. Pattern masking by noise

The GU model is the winning model also for pattern masking by noise as indicated by the adjusted $R^2$ values (Fig. A3). Fig. A4 shows model parameters against SOA values. Means of the Gaussian in the GU model again neither show a systematic change with SOA ($F(11,44) = 0.615, p = 0.806, \eta^2_p = 0.133$) nor significant correlation with masking strength ($t(4) = 1.111, p = 0.329$) (Fig. A4A and D–E). Standard deviation of the Gaussian in the GU model shows changes that resemble the changes in the masking strength (Fig. A4B and D) and there is indeed a relatively weak but significant quadratic trend ($F(1,4) = 8.805, p = 0.041, \eta^2_p = 0.688$). However, only two of the five observers show this trend and a one-way ANOVA of standard deviation yielded no significant effect of SOA ($F(11,44) = 1.350, p = 0.231, \eta^2_p = 0.252$). More importantly, Pearson’s $R$ did not differ significantly from zero ($t(4) = 1.968, p = 0.121$) indicating a rather poor correlation between changes in standard deviation and masking strength. In contrast, as with para-/meta-contrast

![Adjusted R²](image)

**Fig. A1.** Adjusted $R^2$ values obtained from G and GU models averaged across all observers. G represents the Gaussian model whereas GU stands for the Gaussian + Uniform model. Error bars in the average data represent ± SEM, $n = 5$.

![Mean of Gaussian](image)

![Standard Deviation of Gaussian](image)

![Weight of Uniform](image)

![Masking Strength](image)

![Pearson’s R](image)

**Fig. A2.** Parameters of the winning model (GU) as a function of SOA for para-/meta-contrast masking. (A) Mean of the Gaussian in the GU model is shown. (B) Standard deviation of the Gaussian in the GU model. (C) Weight of the Uniform distribution in the GU model. (D) Masking strengths calculated from masking functions in Fig. 5A. (E) Correlations between model parameters and masking strengths. Error bars in the average data represent ± SEM, $n = 5$. 
masking, guess rate correlates strongly with the masking strength (Fig. A4C–E). The stronger the effect, the higher the guess rate, reflected in the weight of the uniform component in the GU model (Fig. A4C and D). This SOA-dependent modulation is significant ($F(11,44) = 17.764, p < 0.001, \eta^2_p = 0.773$). Correlation of the weights with the masking strength was also highly significant ($t(4) = 33.140, p < 0.00001$).

### A.3. Pattern masking by structure

Model performances are given in Fig. A5. Once again, the GU model outperforms all other models. The mean and standard deviation of the Gaussian term and weight of the uniform distribution in the GU model are plotted against SOAs in Fig. A6A–C. Consistently, we observe neither any systematic change in the means with SOA ($F(1,4) = 0.930, p = 0.521, \eta^2_p = 0.189$) nor strong correlation with the masking strength (Pearson’s $R = -0.237 \pm 0.438$), ruling out the possibility of any orientation bias and any relation to a masking effect. We found a significant effect of SOA on the standard deviation ($F(1,4) = 2.640, p = 0.011, \eta^2_p = 0.398$). Finally, the weight of the uniform distribution also changed significantly with SOAs ($F(1,4) = 13.140, p < 0.001, \eta^2_p = 0.767$). The changes in both the standard deviation and the weight of the uniform distribution with SOA correlate well with those of the masking strength (Fig. A6B–E) (Pearson’s $R$ for the standard deviation of the Gaussian = $0.584 \pm 0.062$; for the weight of the Uniform = $0.923 \pm 0.062$). However, it should be noted that a major factor in producing a masking effect is probably due to a reduction in SNR because the weights of the Uniform term more strictly follow the masking strengths (paired $t$-test between Pearson’s $R$ for

---

**Fig. A3.** Adjusted $R^2$ values obtained from G and GU models averaged across all observers for pattern masking by noise. G represents the Gaussian model whereas GU stands for the Gaussian + Uniform model. Error bars in the average data represent $\pm$ SEM, $n = 5$.

**Fig. A4.** Parameters of the winning model (GU) as a function of SOA in pattern masking by noise. (A) Means, and (B) standard deviations of the Gaussian in the GU model. (C) Weight of the Uniform distribution in the GU model. (D) Masking strengths calculated from masking functions in Fig. 7. (E) Correlations between model parameters and masking strengths. Error bars in the average data represent $\pm$ SEM, $n = 5$. 

---

the standard deviation of the Gaussian term and the weight of the Uniform: t(4) = 7.874, p = 0.001). Therefore, these findings suggest that pattern masking by structure also occurs, from a statistical point of view, primarily due to the reduction of target SNR and only partly due to the interference of the target signal with the mask related activity.

In summary, regardless of whether we take the LMS + adjusted $R^2$ or the MLE + BMC approach, the results are almost identical, confirming that our findings are robust and not prone to error due to limitations of the methodology used.

Appendix B

Table B.1 shows the results of the BMC analyses.

Appendix C

One of the anonymous reviewers raised a concern regarding whether the parameter estimates of mixture models would be reliable with the size of our data set. First, as discussed before, two different techniques arrived at similar results. Moreover, in order to assess the reliability of our results with the given data size, we conducted the following simulation studies: First, we synthesized data from a single Gaussian (using the same number of data points as in the empirical data) whose standard deviation changes as a function of different conditions (to simulate different SOAs in the experiments). We then fitted the G and GU models to the synthetic data and we analyzed the BMC differences. We repeated this process (data generation and fitting) multiple times ($N > 100$) and in all cases, model selection based on BMC differences successfully picked the G model as the winning model. An example is shown in Fig. C1. The leftmost panel shows the standard deviation of the Gaussian, that was used to generate the synthetic data (solid line) as well as the standard deviation of the Gaussian in the fitted GU model (markers). Right next to this, the weight of the uniform in the GU model is shown. There seems to be an overestimation of the weights at certain conditions (i.e., SOAs), however, this does not affect adversely the model selection process. In the third panel from left, actual and estimated standard deviations of the Gaussian

Fig. A5. Adjusted $R^2$ values obtained from G, GU, GUCA, and GUNN models in pattern masking by structure. G represents the Gaussian model, GU stands for the Gaussian + Uniform model, GUCA and GUNN represent that the misbinding component is based on either the mask element with the Closest-Angle to the target bar, or on the one which is the Nearest-Neighbor of the target bar. Error bars represent ± SEM, $n = 5$.

Fig. A6. Parameters of the winning model (GU) as a function of SOA in pattern masking by structure. (A) Means, (B) standard deviations of the Gaussian in the GU model. (C) Weight of the Uniform distribution in the GU model. (D) Masking strengths calculated from masking functions in Fig. 10. (E) Correlations between model parameters and masking strengths. Error bars in the average data represent ± SEM, $n = 5$. 

Fig. A6.
Table B.1
BMC differences of all models from G model and corresponding Bayes factors in all masking types and for each observer are tabulated.

<table>
<thead>
<tr>
<th>Observer</th>
<th>Para-/meta-contrast masking</th>
<th>Masking by noise</th>
<th>Masking by pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ABMC</td>
<td>Bayes factor</td>
<td>ABMC</td>
</tr>
<tr>
<td></td>
<td>GU-G</td>
<td>GU/G</td>
<td>GU-G</td>
</tr>
<tr>
<td>SA</td>
<td>10.26</td>
<td>28,684</td>
<td>1.39</td>
</tr>
<tr>
<td>FG</td>
<td>8.27</td>
<td>3,909</td>
<td>4.88</td>
</tr>
<tr>
<td>GJ</td>
<td>6.50</td>
<td>663</td>
<td>6.40</td>
</tr>
<tr>
<td>Average</td>
<td>10.59</td>
<td>39,633</td>
<td>6.37</td>
</tr>
</tbody>
</table>

Fig. C1. Model fitting and model comparison by using synthetic data. See text for detailed explanations.

Fig. C2. Model fitting and model comparison by using synthetic data generated from a GU model with varying standard deviation for the Gaussian term as a function of SOA, and a constant weight for the Uniform component. See text for details.
in the G model are plotted. As expected they nicely match. Finally, in the rightmost panel, the BMC differences averaged across “synthetic subjects” (GU-G) are given. All points are below zero, indicating that the generated data is less likely to be drawn from a GU distribution.

Second, we synthesized data from a GU model with different weights of the Uniform component. We considered two different scenarios: (i) varying standard deviation for the Gaussian term as a function of SOA, and a constant weight for the Uniform component (Fig. C2), (ii) a constant standard deviation for the Gaussian, and a varying weight for the Uniform (Fig. C3). We present two cases from each scenario to demonstrate that the usage of mixture models along with Bayesian model comparison techniques is warranted. The slight overestimation of the weight of the Uniform component at certain SOAs (depicted as “conditions” in the figures here) does not hinder selection of the correct source of the data at hand. In fact, whenever there is an overestimation, likelihood of the GU model dramatically decreases, as indicated by huge drops in BMC differences in the rightmost panels.

References


