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Confidence in masked orientation discrimination decisions is informed by both evidence and visibility

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Abstract

How do human observers determine their degree of belief of being correct in a visual discrimination decision, i.e. their confidence? According to prominent theories of confidence, the quality of stimulation should be positively related to confidence in correct decisions and negatively to confidence in incorrect decisions. However, in a backwards-masked orientation discrimination task with varying stimulus-onset asynchrony (SOA), we observed that confidence in incorrect decisions increased with stimulus quality as well. Model fitting to decision and confidence data revealed that the best explanation for the present data was the new weighted evidence and visibility model, according to which confidence is determined by evidence about the orientation as well as the general visibility of the stimulus. Signal detection models, post-decisional accumulation models, two channel models, and decision-time based models were all unable to explain the pattern of confidence as a function of SOA and decision correctness. We suggest that the metacognitive system combines several cues to being correct in visual discrimination decisions to calculate decision confidence.

Keywords: metacognition; confidence; signal detection theory; cognitive modeling, visibility

39 Introduction

40 Humans are usually faced with the need to make decisions about stimuli based on
41 distorted or ambiguous sensory signals. To deal with that uncertainty, various strategies exist,
42 such as looking the stimulus for a longer period of time, or asking other persons about their
43 opinions. In order to know when these strategies are appropriate, observers need to have a
44 sense for the probability that their decisions will be correct. The resulting subjective belief
45 that a decision is correct is what we here refer to as *confidence* (Pouget, Drugowitsch, &
46 Kepecs, 2016). To assess confidence experimentally, the standard procedure is to present
47 observers in several trials with always one out of a set of two possible stimuli. Observers are
48 asked to make a decision which of the two stimuli occurred and to indicate how confident
49 they are about the accuracy of that decision (Baranski & Petrusic, 1994; Fleming & Dolan,
50 2012; Kepecs & Mainen, 2012). How do observers determine their degree of belief that a
51 discrimination decision is correct? Although numerous different theories have been proposed
52 in recent years (Fleming & Daw, 2016; Jang, Wallsten, & Huber, 2012; Kiani, Corthell, &
53 Shadlen, 2014; Maniscalco & Lau, 2016; Moran, Teodorescu, & Usher, 2015; Paz, Insabato,
54 Zylberberg, Deco, & Sigman, 2016; Pleskac & Busemeyer, 2010; Sanders, Hangya, &
55 Kepecs, 2016), there is still no consensus what is the explanatory mechanism. In the present
56 study, we suggest a novel alternative model for confidence in visual discrimination decisions,
57 namely the *weighted evidence and visibility model* (WEV-model).

58 Signal detection theory (SDT) and related models

59 The most prominent class of models of confidence relies on SDT (Green & Swets,
60 1966; Macmillan & Creelman, 2005; Wickens, 2002). SDT models assume the same

mechanism underlying the discrimination decision, but they extend SDT in different ways to account for confidence.

The mechanism proposed by SDT for making a discrimination decision is the following (Green & Swets, 1966; Macmillan & Creelman, 2005; Wickens, 2002): First, the stimulus generates sensory data within the visual system of the observer. Not all of the sensory data caused by the stimulus are relevant for the discrimination decision. Those sensory data that are relevant for the task are transformed into discrimination evidence, a continuous internal variable that differentiates between the two stimulus alternatives (Gold & Shadlen, 2007; Wickens, 2002). As there is noise in the system, discrimination evidence varies across presentations of the stimuli, which is why it is described as a random sample out of one of two probability distributions, one for each stimulus. If the observer is unable to differentiate between the stimuli, the two distributions created by the two stimuli are identical. The better the observer is able to differentiate between the two possible stimuli, the greater is the distance between the two distributions. To select a response, it is assumed that observers compare their sample of evidence against a set of criteria. Observers respond “A” if their sample is greater than the criterion, and “B” otherwise.

How can SDT be extended to account for confidence as well? The various different proposals can be assorted into three categories (see Fig 1):

(i) Discrimination decision and confidence are based on an identical sample of discrimination evidence (*SDT rating model*)

(ii) Confidence is based on the same sample of discrimination evidence as the discrimination decision, but the sample available for confidence is distorted or overlaid with noise (*noisy SDT models*).

(iii) Confidence is based on a second sample of discrimination evidence (*two channel models*).

Fig. 1. Three different extensions of the original signal detection model to account for confidence judgments.

According to (i), the SDT rating model, decision options and levels of confidence are considered to form an ordered set of responses such as “I am sure it is A”, “I am guessing A”, “I am guessing B”, “I am sure it is B”. Each adjacent pair of response options is delineated by one criterion. Both the discrimination decision and confidence are selected by the comparison of a single sample of discrimination evidence with the set of criteria. This means observers respond “I am guessing B” if the sample falls between that criterion separating “I am guessing B” from “I am guessing A” and that criterion separating “I am guessing B” from “I am sure it is B”.

Proposal (ii) is shared by several models that we collectively refer to here as noisy SDT models. These models assume confidence is informed by the sample of discrimination evidence used to select the discrimination decision, but the sample is distorted, incomplete, or overlaid with noise. The degree of confidence is then determined by comparing the distorted sample against a set of confidence criteria. The different theories categorized as noisy SDT model imply different mechanisms why the discrimination evidence used for confidence is less informative than the evidence for the discrimination decision: First, the sample could be overlaid by unsystematic noise (Hebart, Schriever, Donner, & Haynes, 2016; Sanders et al.,

2016). Second, the discrimination evidence might be reduced (Maniscalco & Lau, 2016).

Finally, confidence could be based exclusively on discrimination evidence in favor of the selected option, but not on evidence against it (Zylberberg, Barttfeld, & Sigman, 2012).

Proposal (iii) is a tenet of models that we here refer to as two channel models. These models were motivated by the observation that observers occasionally realize that they made an error, which is not possible within the SDT rating model or the noisy SDT model (Fleming & Daw, 2016; Yeung & Summerfield, 2012). Two channel models are characterized by the assumption that confidence is not based on the sample of discrimination evidence used to make the discrimination decision. Instead, confidence is based on a second sample of discrimination evidence generated in parallel to first one. Although the term two channel model seems to suggest that the parallel samples are generated by two separate processes (Maniscalco & Lau, 2016), it is also possible that the same process generates the sample for the discrimination decision first, and the sample for confidence afterwards (Moran et al., 2015). Observers are confident to the degree that the second sample confirms the discrimination decision. While it is sometimes implied that the discrimination evidence used for confidence is stochastically independent from the discrimination evidence used in the decision (Rausch & Zehetleitner, 2017), other models allow for a correlation between the two samples (Fleming & Daw, 2016; Jang et al., 2012).

The interaction between the quality of the stimulus and the correctness of the decision

How can SDT models of confidence be tested? A benchmark test may be found in the interaction between an experimental manipulation of the quality of stimulation and correctness of the decision (Moran et al., 2015). Examples for manipulations of the quality of stimulation are the contrast between stimulus and background, or the presentation time. SDT and many models that assume that confidence is based on discrimination evidence predict the

same qualitative pattern (Kellen & Klauer, 2015; Kepecs, Uchida, Zariwala, & Mainen, 2008; Sanders et al., 2016): When the discrimination decision is correct, confidence should be positively associated with stimulus quality. In contrast, in incorrect trials, the correlation between confidence and stimulus quality should be negative. The reason for the interaction can be seen from Fig. 2. To be confident in a discrimination decision, the sample of discrimination evidence must be more extreme than the criteria separating decisions without confidence from decisions with confidence. When the stimulus quality is low so the two stimuli are very hard to distinguish, the two distributions of discrimination evidence overlap almost entirely (left panel). When the stimulus quality is better, the two distributions are shifted away from each other (right panel). Therefore, greater portions of the distributions extend beyond the criteria for confidence in the correct decision, implying that confidence in the correct decision becomes more and more likely. However, when distance between the two distributions is large, the portions of the distributions that exceed the confidence criteria for incorrect decisions, which are located at the other side of the distributions, become smaller and smaller (highlighted in black). As a consequence, when stimulus quality increases, confidence in incorrect decisions will become less likely.

Fig 2. Distributions of discrimination evidence when the quality of the stimulus is low (left panel) and high (right panel). The areas in black highlight the probabilities of an incorrect decision while being confident.

Is there empirical support for such an interaction pattern? Previous studies concurrently observed the predicted positive correlation between stimulus quality and confidence in *correct decisions* across a variety of tasks (Kiani et al., 2014; Moran et al., 2015; Rausch & Zehetleitner, 2016; Sanders et al., 2016). However, these studies were inconsistent regarding the predicted negative correlation between stimulus quality and confidence in *incorrect decisions*: The correlation was negative as predicted by SDT in an auditory discrimination task and a general knowledge task (Sanders et al., 2016) as well as in a discrimination task about the relative amount of white and black areas in a visual texture (Moran et al., 2015). However, in contrast to SDT, coherence of motion was positively, not negatively associated with confidence in incorrect trials in a random-dot motion discrimination task (Kiani et al., 2014). Further, in a low-contrast orientation discrimination task, the average correlation between stimulus contrast and confidence in incorrect responses was close to zero with a narrow confidence interval (Rausch & Zehetleitner, 2016). Overall, the observations of both positive and negative correlations between stimulus quality and confidence in incorrect decisions pose a challenge to models of confidence derived from SDT.

The weighted evidence and visibility model

The present study proposes a new model of confidence in visual discrimination decisions, the weighted evidence and visibility model (WEV). The core idea is that confidence judgments are influenced by two internal variables: the discrimination evidence as well as the visibility of the stimulus (see Fig. 3).

Fig 3. The weighted evidence and visibility model. The stimulus varies in two aspects: The stimulus category (symbolized here as “A” and “B”) and a manipulation of stimulus quality (symbolized by the noise dots). The stimulus is assumed to generate two internal variables: The discrimination evidence, a continuous variable that differentiates between the categories “A” and “B”, and the visibility, a continuous variable that differentiates between “no visibility of the stimulus” and “full visibility”. The discrimination evidence is used to select a discrimination response about the stimulus category. Confidence judgments about the correctness of the discrimination decision however are based on both discrimination evidence as well as visibility.

The reason why visibility is informative for confidence is because stimuli are always comprised of several features: e.g. size, form, color, brightness, etc. In discrimination tasks, each stimulus falls into one out of two categories, and observers need to make a decision which category the present stimulus belongs to. Although only one or two features usually determine the category of the stimulus, the visual system creates sensory data not only about task-relevant, but also about task-irrelevant features (Marshall & Bays, 2013; Xu, 2010). To make a decision about the two categories of the stimulus, the task-relevant sensory data is transformed into discrimination evidence, an internal variable that differentiates between the two stimulus categories (Wickens, 2002). Task-irrelevant sensory data are not informative about the stimulus category and therefore should not contribute to the discrimination

evidence. However, task-irrelevant sensory data are not entirely useless; they are informative about the *quality of stimulation*. This is particularly true for experiments where the category of the stimulus and the quality of stimulation are both experimentally varied across trials. When many features of the stimulus are highly visible, it is reasonable to assume that the task-relevant stimulus feature was correctly perceived, and thus a high degree of confidence is appropriate. Likewise, when the task-irrelevant features of the stimulus cannot be perceived, it is likely that the discrimination evidence is uninformative or even misleading.

Therefore, the WEV-model assumes that confidence is not only based on discrimination evidence. The second source of input is as an estimate of the physical quality of the stimulus, which we refer to here as the visibility of the stimulus. For computational simplicity, the WEV-model assumes that discrimination evidence and visibility both depend on the quality of stimulation, but are stochastically independent when the stimulus quality is held constant. Stochastic independence may be the consequence of parallel processing of stimulus features in the visual system (Kyllingsbæk & Bundesen, 2007). To determine the degree of confidence, discrimination evidence and visibility of the stimulus are weighted and combined to a decision variable. As the visibility of the stimulus is determined by the manipulation of the stimulus quality, but not by the stimulus category, a strong weight on visibility implies a positive correlation between stimulus quality and confidence in incorrect decisions. In contrast, a strong weight on evidence results in a negative correlation between stimulus quality and confidence in incorrect decisions. Thus, the weighting of discrimination evidence and visibility allows the WEV-model to be consistent with both positive and negative correlation patterns.

Confidence and decision time

212   An alternative explanation for positive correlations between stimulus quality and
213 confidence in incorrect decisions is provided by two sequential sampling models of decision
214 making (Ratcliff, Smith, Brown, & McKoon, 2016): The diffusion model with internal
215 deadlines (Ratcliff, 1978) and the bounded accumulation model (Kiani et al., 2014). These
216 models share the assumption that that confidence is informed by elapsed time before a
217 decision is reached. According to the internal deadlines model, observers set themselves
218 variable deadlines for making the decision: When the decision is made before any of the
219 deadlines has passed, the observer feels maximally confident that the decision is correct. The
220 more deadlines are missed, the less confident is the observer that the decision is correct
221 (Ratcliff, 1978). Can internal deadlines explain positive correlations between stimulus quality
222 and confidence in incorrect decisions? As the model assumes that confidence is informed
223 only by decision time, when increasing stimulus quality speeds up decision time for incorrect
224 decisions, increasing stimulus quality should also make observers more confident in incorrect
225 decisions. In contrast, when increasing stimulus quality slows down decision time for
226 incorrect decisions, increasing stimulus quality should decrease confidence in incorrect
227 decisions. At a consequence, the internal deadlines model can be tested by comparing the
228 correlation between stimulus quality and confidence with the correlation between reaction
229 time and confidence. If the model was correct, the correlations should be of different signs.

230   The bounded accumulation model implies a more complex relationship between
231 decision times and confidence. There, it is argued that sensory evidence is accumulated
232 within two processes. The first process hitting a decision boundary determines which of the
233 two stimulus categories is selected. Over time, observers learn to associate decision times and
234 states of the losing accumulator with the probability of being correct. When observers make a
235 confidence judgment, they compare the decision time and the state of losing accumulator
236 with the distributions of decision times and accumulator states of correct and incorrect

decisions they have learned over time. When current decision time and accumulator state are more likely to stem from the distributions known from correct trials than from those of incorrect trials, observers are confident that the decision is correct (Kiani et al., 2014; van den Berg, Zylberberg, Kiani, Shadlen, & Wolpert, 2016; Van Den Berg et al., 2016). Can the bounded accumulation model explain positive correlations between stimulus quality and confidence in incorrect decisions? The state of the losing accumulator alone cannot account for positive correlations because it consists of discrimination evidence, which implies a negative correlation between stimulus quality and confidence in incorrect decisions just as SDT does. However, the positive correlations between stimulus quality and confidence in incorrect decisions can be explained by observers learning the distribution of decision times. There are two possibilities. First, observers might learn that correct decisions are faster than incorrect decisions. In this case, if increasing stimulus quality speeds up decision times for incorrect decisions, confidence in incorrect decisions should be increased as well. Second, observers could learn that correct decisions are slower compared to incorrect decisions. In this case, confidence in incorrect decisions should increase with stimulus quality only if increasing stimulus quality slows down decision times for incorrect decisions.

To summarize, models of confidence based on decision times are in principle consistent with positive correlations between stimulus quality and confidence in incorrect decisions. However, positive correlations between stimulus quality and confidence imply specific patterns of decision times, which can be tested.

Rationale of the present study

The present study was designed to test if the WEV-model provides a better account of confidence in visual discrimination decisions than previously established models of confidence. For this purpose, we asked participants to perform a masked orientation

discrimination task. To manipulate stimulus quality, we varied the stimulus-onset-asynchrony (SOA) between the target stimulus and a backward mask. In Exp. 1, participants reported the orientation of the stimuli as well as their confidence in being correct with just one single response. In Exp. 2, confidence judgments were made after the discrimination judgment. In both experiments, the associations between SOA and confidence and SOA and response times were assessed separately in correct and incorrect decisions. Moreover, we formally assessed goodness-of-fit of seven different models fitted separately to the orientation responses and confidence reports of each single participant. The seven models included the WEV-model, the SDT model, the noisy SDT model, the postdecisional accumulation model, and the two channel model. In addition, two variants of the WEV-model and the SDT model were used, one model where the variability of discrimination evidence increased as a function of stimulus quality, and one where the variability remained constant. These two models with SOA-dependent variance of discrimination evidence were included because pilot studies revealed that allowing variance to increase with SOA improved model fit. Although previous studies determined the parameters of the postdecisional accumulation models based on orientation responses, confidence, and response times (Moran et al., 2015; Pleskac & Busemeyer, 2010), the present study did not model response times, as the WEV model and the SDT models do not make a prediction about response times, and model comparisons need to be made on the same data .

We hypothesized that if the WEV-model provides a better account of confidence in masked orientation decisions than any of the other five competing models, the two variants of the WEV-model should result in better goodness-of-fit measures than any of the competing models. If confidence was informed only by discrimination evidence, as argued by SDT and related models, the correlation between SOA and confidence in incorrect trials should be negative. A positive correlation of SOA and confidence in incorrect trials would be consistent

286 with the WEV-model. Finally, if the correlations between SOA and confidence in incorrect
287 trials can be explained by confidence being informed by decision times, the correlations
288 between SOA and confidence should be consistent to the correlation between SOA and
289 reaction time.

290

Experiment 1

Material and Methods

Participants. 20 participants (3 male, 17 female) took part in the experiment. The age of the participants ranged between 18 and 40 years ($M = 23.3$). All participants reported normal or corrected-to-normal vision, no history of neuropsychological or psychiatric disorders and not to be on psychoactive medication. All participants gave written informed consent and received either course credits or €8 per hour for participation.

Apparatus and stimuli. The experiment was performed in a darkened room. The stimuli were presented on a Display++ LCD monitor (Cambridge Research Systems, UK) with screen diagonal of 32'' set at a refresh rate of 120 Hz. The distance between the monitor and the participant was approximately 60 cm. The experiment was conducted using PsychoPy v.1.83.04 (Peirce, 2007, 2008) on a Fujitsu ESPRIMO P756/E90+ desktop computer with Windows 8.1. The target stimulus was a square (size $3^\circ \times 3^\circ$), textured with a sinusoidal grating with one cycle per degree of visual angle (maximal luminance: 64 cd/m²; minimal luminance: 21 cd/m²). The mask consisted of a square ($4^\circ \times 4^\circ$) with a black (0 cd/m²) and white (88 cd/m²) checkered pattern consisting of 6 columns and rows. All stimuli were presented at fixation in front of a grey (44 cd/m²) background. The orientation of the grating varied randomly between horizontal or vertical. The participants simultaneously reported the orientation of the target and their confidence in being correct a Cyborg V1 joystick (Cyborg Gaming, UK). Confidence was recorded using a continuous scale because continuous scales provide a maximum amount of information per single trial (Rausch & Zehetleitner, 2014).

Fig 4. Trial structure of Exp. 1

Trial structure. The time course of one trial is shown in Fig. 4. Each trial began with the presentation of a fixation cross for 1,000 ms. Then the discrimination target stimulus was shown for a short period of time until it was replaced by the mask. There were five different possible SOAs, time periods between target onset and mask onset: 8.3, 16.7, 33.3, 66.7 and 133.3 ms. The mask was always presented for 500 ms. When the mask disappeared, two visual analog scales were displayed on the screen. The upper scale represented the response that the orientation of the target was vertical and the bottom one represented the response that the orientation of the target was horizontal. Observers responded to the orientation task by moving the joystick back and forth, moving an index from the lower to the upper scale and vice versa. The ends of both scales were labelled as *unsure* and *sure*. Observers could report their confidence by moving the joystick towards the left or to the right, thus moving the index on the scales. To avoid any bias by an initial position of the index, the index only appeared when observers started moving the joystick back or forth. The orientation response and degree of confidence were recorded when observers pulled the trigger of the joystick. Finally, if the orientation response was wrong, the trial ended by the presentation of the word *error* for 1,000 ms.

Design and procedure. Participants were instructed to report the orientation of the grating and their confidence in being correct at the orientation judgment as accurately as possible without time pressure. The experiment consisted of one training block and 9 experimental blocks of 60 trials each. Each SOA featured 12 times in each block in random order. The orientation of the target stimulus varied randomly across trials. After each block, the percentage of errors was displayed to provide participants with feedback about their accuracy.

Analysis

Correlation analysis. To assess the relation between confidence and SOA, we calculated the correlation between confidence and SOA separately for each participant and for correct and incorrect decision. Correlations were measured by the Goodman and Kruskal's gamma coefficient Γ , as Γ does not make any scaling assumptions beyond the ordinal level and can attain its maximum value irrespective of ties (Nelson, 1984). As a second step, Bayesian equivalents of t-tests were used to test if the mean Γ was different from zero. As recommended as standard prior, a Cauchy distribution with a scale parameter of 1 was assumed as prior distribution for standardized effect sizes (Rouder, Speckman, Sun, Morey, & Iverson, 2009). The same procedure was used to assess the correlation between SOA and reaction time. In addition, Markov chain Monte Carlo resampling was used to determine means and 95% credible intervals of the posterior distribution. These analyses were conducted using the R library *BayesFactor* (Morey & Rouder, 2014).

Modeling analysis. We fitted seven different models derived from SDT to the joint distributions of orientation responses and confidence data.

- (i) the SDT rating model
- (ii) the noisy SDT model

- (iii) the SDT model with SOA-dependent variance of evidence
- (iv) the WEV-model
- (v) the WEV-model with SOA-dependent variance of evidence
- (vi) the two channel model
- (vii) the postdecisional accumulation model

In all seven models, it was assumed that each presentation of the stimulus creates a sample of discrimination evidence x drawn from a Gaussian distribution. The location of the distribution is determined by the stimulus category $S \in \{0,1\}$ as well as the sensitivity parameter d specific to each SOA. Thus, each model involves five different sensitivity parameters $d_1 - d_5$, one for each SOA. The mean of the distribution was calculated as $(S - \frac{1}{2}) \times d_i$: Thus, when $S = 1$, the distribution is centered at $d/2$, and at $-d/2$ when $S = 0$. In model (iii) and (v), the variance s^2 of the distributions of x increases as a function of d : $s^2 = 1 + k \times d_i^2$, where k is a free parameter quantifying the slope of the increase of variance with d . These two models were included into the analysis because the analysis of pilot experiments revealed that assuming the variance of evidence increases as a function SOA improved model fits of the SDT and WEV-model. In all other models, the variance s^2 was set to 1. In all models, participants' response R is assumed to be 0 when x is lower than the primary task criterion θ , and 1 otherwise.

A degree of confidence is determined by comparing the decision variable y against a set of confidence criteria c . Each confidence criterion delineates between two adjacent confidence categories, e.g. participants select confidence category 2 if y falls between c_1 (which separates category 1 and 2) and c_2 (which separates category 2 and 3). To be consistent with the standard SDT rating model (Green & Swets, 1966), two separate sets of

confidence criteria were assumed, one for each response option. The different models are characterized by the way how y is determined:

- According to SDT rating model and the SDT model with SOA-dependent variance of evidence, y is identical to x .
- According to the noisy SDT model, y is sampled from a Gaussian distribution, with a mean of x and with the standard deviation σ , which is an additional free parameter.
- According to the WEV model and the WEV-model with SOA-dependent variance of discrimination evidence, y is again sampled from a Gaussian distribution with the standard deviation σ . The mean of the distribution from which y is drawn is calculated as $(1 - w) \times x + w \times (2R - 1) \times (d_i - \text{mean}(d))$. The parameter w describes the degree to which participants rely on discrimination evidence or on visibility when they report their degree of confidence. When $w = 0$, then the formulae reduces to $y = x$; meaning the model is then identical to the noisy SDT model. The closer w is to 1, the more y depends on the term $(2R - 1) \times (d_i - \text{mean}(d))$. The term $d_i - \text{mean}(d)$ ensures that y depends on the quality of stimulation, as indexed by d_i , independent of x . The term $2R - 1$ ensures that highly visible stimuli tend to shift y in a way that high confident responses are more likely, and likewise, low visible stimuli shift y in a way that the probability of low confident responses increases.
- According to the two channel model, y is stochastically independently from x . The mean of the distribution of y is given by $a \times d_i$, where a is a free parameter that expresses the fraction of signal available to the second channel compared to the signal available to the first channel. The variance of y is set at 1.
- According to the postdecisional accumulation model, y is again sampled from a Gaussian distribution. The mean of the distribution is given by $x + (2S -$

1) $\times d_i \times b$, where b indicates the amount of postdecisional accumulation, and the term $2S - 1$ ensures that postdecisional accumulation tends to decrease y when $S = 0$, and to increase y when $S = 1$. The variance of distribution of y is b^2 .

Model fitting was performed separately for each single participant. The fitting procedure involved the following computational steps. First, the continuous confidence ratings were discretized by dividing the continuous scale into 5 equal partitions. Second, the frequency of each confidence category was calculated for both orientations of the stimulus and the orientation response. Third, for each model, the set of parameters was determined that minimized the negative log-likelihood of the data. To compute the likelihood, two common assumptions were made (Dorfman & Alf, 1969; Maniscalco & Lau, 2016): (i) responses in each trial are independent from each other and (ii) the joint probability of a task response and confidence given the stimulus is constant across trials. Formally, the negative log-likelihood of a set of parameters given primary task responses and confidence $\log(\mathcal{L}(p|R, C))$ is given by

$$\log(\mathcal{L}(p|R, C)) \propto \sum_{i,j,k} \log(P(R_i, C_j|S_k, p)) \times n(R_i, C_j|S_k) \quad (1)$$

where $P(R_i, C_j|S_k, p)$ denotes the probability of a primary task response in conjunction with a specific degree of confidence given the stimulus and the set of parameters, and $n(R_i, C_j|S_k)$ indicates the frequency how often the participants give a specific response in conjunction with a specific confidence category given the stimulus. Minimization of the negative log-likelihood was performed using a general SIMPLEX minimization routine implemented in the R function `optim` (Nelder & Mead, 1965). The calculation of $P(R_i, C_j|S_k, p)$ is specific to each model and is described in the Appendix.

The relative goodness-of-fit of the seven candidate models was assessed using the Bayes information criterion (Schwarz, 1978) and the Akaike information criterion (Akaike,

1974). Conceptually, the BIC measures the degree of belief that a certain model is the true data-generating model relative to the other models under comparison, assuming that the true generative model is among the set of candidate models. In contrast, the AIC measures the loss of information when the true generative model is approximated by the candidate model. We used the AIC_c , a variant of AIC that corrects for finite sample sizes (Burnham & Anderson, 2002). BIC and AIC_c take into account descriptive accuracy (i.e. goodness of fit) and parsimony (i.e. smallest number of parameters), but the BIC favors parsimony more heavily than the AIC_c does. BIC and AIC_c are given by the formulae:

$$BIC = -2 \log(\mathcal{L}(p|R, C)) + k \log(n) \quad (2)$$

$$AIC_c = -2 \log(\mathcal{L}(p|R, C)) + 2k + \left(\frac{2k(k+1)}{(n-k-1)} \right) \quad (3)$$

where k indicates the number of parameters and n the number of observations.

To compare the two WEV-models against the five alternative models, Bayes factors were used to test if the WEV-models are on average associated with better BICs and AIC_c s. Again, we used the Bayesian equivalents of t-Tests, assuming a standard Cauchy distribution as prior for standardized effect sizes (Rouder et al., 2009), implemented in the R package *BayesFactor* (Morey & Rouder, 2014). In addition, we report means and the 95% credible interval of the posterior distribution of the mean BIC and AIC_c difference between models.

All analyses were conducted using the free software R (R Core Team, 2014).

Results

Two participants were excluded from the analysis because their discrimination performance was not above chance level, BF_{10} 's $\leq .20$. For the remaining 18 participants, discrimination performance ranged between chance level at an SOA of 8.3 ms ($M = 49.7\%$, $SD = 6.5$) and ceiling at the maximum SOA of 133.3 ms ($M = 97.4\%$, $SD = 6.7$). Confidence

judgments averaged 11.5% ($SD = 11.7$) of the width of the visual analog scale at an SOA of 8.3 ms and increased to a mean of 90.2% ($SD = 14.0$) at an SOA of 133.3 ms.

Correlation between SOA and confidence. As can be seen from the left panel of Fig. 5, confidence increased as a function of SOA in correct trials as well as in incorrect trials, although in the latter case to a lesser extent. The average correlation coefficient was large for correct trials, $M = .80$, $SD = .08$, and medium for incorrect trials, $M = .38$, $SD = .19$. A Bayesian analysis indicated decisive evidence that the average correlation coefficients were different from zero for correct trials, posterior of the mean 95% $CI = [.76 .84]$, $BF_{10} = 3.57 \cdot 10^{15}$, as well as incorrect trials, posterior of the mean 95% $CI = [.27 .46]$, $BF_{10} = 8.77 \cdot 10^4$.

Fig. 5. Mean confidence (left panel) and response time (right panel) depending on stimulus-onset-asynchrony (X-axis) and accuracy of the discrimination decision (different lines and symbols).

Correlation between SOA and reaction times. As shown by the right panel of Fig. 5, correct responses were faster than incorrect responses, posterior of the mean RT difference 95% $CI = [54.9 262.2]$, $BF_{10} = 11.3$. Correct responses also appeared to become faster with increasing SOA. However, the average correlation was only weakly negative, $M = -.11$, $SD = .26$, and there was insufficient evidence to ascertain if the average correlation was different from 0, posterior of the mean 95% $CI = [-.22 .02]$, $BF_{10} = .74$. Concerning incorrect

responses, Fig. 5. suggests that response times remained constant for shorter SOAs between 8.3 and 33.0, and sharply increased for the longer SOAs. However, the average correlation was negligibly small, $M = .05$, $SD = .14$. The reason is that the number of errors at longer SOAs was low, which is why errors at shorter SOAs contributed more strongly to the correlation coefficients. Consequently, there was insufficient evidence to ascertain if the average correlation was zero, posterior of the mean 95% $CI = [-.02 .11]$, $BF_{10} = .49$.

Modeling results. As suggested by upper left and upper central panel of Fig. 6, the only two models that were able to reproduce the increase of confidence with SOA in incorrect trials were the WEV-model and the WEV-model with SOA-dependent variance of discrimination evidence. All the other models predicted a decrease of confidence in incorrect trials with SOA, but the decrease was not supported by the data.

477 Fig. 6. Mean confidence predicted by the seven models (in separate panels) depending on stimulus-
478 onset-asynchrony (x-Axis) and accuracy of the discrimination response in Exp. 1. Straight lines
479 indicate the prediction for correct trials, dotted lines in incorrect trials. Circles indicate observed
480 confidence in correct trials, and triangles in incorrect trials. Error bars indicate 1 SEM.

481 Fig. 7 shows that the two flavors of the WEV-model were able to reproduce the
482 correlation between SOA and confidence on the level of each single participant. The other
483 models systematically failed to account for the degree of confidence in incorrect decisions.

Fig. 7. Observed gamma correlation coefficients between SOA and confidence as a function of the predicted gamma correlation coefficient for the different models in separate panels in Exp. 1. Each symbol represents data from one participant. Error bars indicate the standard error of the correlation coefficient.

The two WEV-models also fitted the data best in terms of BIC and AIC_c: The best model overall was the WEV-model with SOA-dependent variance of discrimination

evidence, $BIC: M = 1386$; $AIC_c: M = 1314$, followed by the WEV-model with constant variance; $BIC: M = 1388$, $AIC_c: M = 1320$. The third-best model was the SDT model with SOA-dependent variance of evidence, but its fit to the data was worse according to both metrics ($BIC: M = 1425$; $AIC_c: M = 1362$). All the other models performed even worse (all BIC 's: $M \geq 1506$; all AIC_c 's: $M \geq 1447$).

A series of Bayes factors was used to compare AIC_c and BIC of the WEV-model with SOA-dependent variance of discrimination evidence against all the other six models. The Bayes factors revealed some evidence against a difference in model fit between the WEV-model with SOA-dependent variance and the WEV-model with constant variance:

- BIC : posterior of the mean ΔBIC : 95% $CI = [-14.1 \ 11.4]$, $BF_{10} = .18$

- AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-18.1 \ 7.6]$, $BF_{10} = .25$.

However, the Bayes factors also indicated very strong evidence that the WEV-model with SOA-dependent variance fitted the data better than each of the other five models:

- the SDT model with SOA-dependent variance of discrimination evidence:

- BIC : posterior of the mean ΔBIC : 95% $CI = [-55.1 \ -18.9]$, $BF_{10} = 109.2$

- AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-63.6 \ -27.1]$, $BF_{10} = 695.8$

- the SDT rating model:

- BIC : posterior of the mean ΔBIC : 95% $CI = [-162.9 \ -67.6]$, $BF_{10} = 546.9$

- AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-175.3 \ -79.3]$, $BF_{10} = 1.5 \cdot 10^3$

- the postdecisional accumulation model:

- BIC : posterior of the mean ΔBIC : 95% $CI = [-167.9 \ -71.8]$, $BF_{10} = 801.4$

- AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-176.8 \ -79.9]$, $BF_{10} = 1.6 \cdot 10^3$

- the noisy SDT model:

- BIC : posterior of the mean ΔBIC : 95% $CI = [-168.8 \ -73.0]$, $BF_{10} = 897.6$

- 515   – AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-177.5 -81.2]$, $BF_{10} = 1.8 \cdot 10^3$
- 516   • the two channel model:
- 517   – BIC : posterior of the mean ΔBIC : 95% $CI = [-177.4 -80.3]$, $BF_{10} = 1.5 \cdot 10^3$
- 518   – AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-184.7 -88.8]$, $BF_{10} = 3.0 \cdot 10^3$.

519 Discussion

520   Exp. 1 revealed strong evidence that the WEV-model with SOA-dependent variance
 521 of discrimination evidence provides a better account for confidence in masked orientation
 522 discrimination decisions than the SDT model, the noisy SDT model, the postdecisional
 523 accumulation model, the two channel model. Moreover, there was decisive evidence that
 524 longer SOAs increased confidence in both correct as well as incorrect responses, an
 525 observation consistent with the WEV-model but not in accordance with the SDT rating model
 526 and many other confidence models. Concerning response times, there was insufficient
 527 evidence to determine if there was a correlation between SOA and response time in correct or
 528 incorrect trials.

529   Can the positive correlation between SOA and confidence in incorrect decisions be
 530 explained by the WEV-model alone, or are models based on decision time able to provide an
 531 explanation as well? Both the internal deadlines model and the bounded accumulation model
 532 could only account for the confidence data if there had been a negative correlation between
 533 SOA and response times. The reason is that according to the internal deadlines model, when
 534 observers are more confident, it means the decision process was faster so fewer internal
 535 deadlines were missed. According to the bounded accumulation model, as correct responses
 536 were faster than incorrect responses, observers would have associated fast responses with a
 537 greater probability of a correct response, meaning confidence in incorrect decisions would
 538 increase with SOA only if responses times decreased with SOA. Unfortunately, the evidence

was inconclusive if the correlation of RT and SOA was absent, although the credible interval indicated that if there was a negative correlation, its magnitude would be close to zero. Nevertheless, as there is still the possibility of a correlation between SOA and response times, the deadline diffusion model and the bounded accumulation model cannot be ruled out as explanations of the positive correlation between SOA and confidence in incorrect decisions in Exp. 1. There are several reasons why the correlation between SOA and response times might remain undetected in Exp. 1. First, it would be expected that longer SOAs speed up correct responses. However, in Exp. 1, there was insufficient evidence for such a correlation, too. This may indicate that the assessment of response times might not be very precise. An obstacle to assessing response times with precision is that observers in Exp. 1 had to make two decisions at the same time, one about the orientation of the stimulus and one about their degree of confidence. As a consequence, response times in Exp. 1 reflect not only the time needed to make a decision about the orientation of the stimulus, but also time required to select a degree of confidence. The decision time related to confidence might obscure the correlation between SOA and decision time related to the orientation of the stimulus (Kiani et al., 2014). For this reason, in Exp. 2, observers were instructed to report their degree of confidence only after the orientation response.

Is it possible that the simultaneous measurement of confidence and orientation responses interfered with the reported degree of confidence as well, not only with its timing? In line with this hypothesis, the other study to observe a positive correlation between confidence in incorrect decisions and stimulus quality assessed confidence and task response by one single response as well (Kiani et al., 2014). Those studies to find a negative correlation all assessed confidence only after the orientation response (Moran et al., 2015; Sanders et al., 2016). Previous studies offered two explanations why measuring confidence simultaneously with or subsequent to the decision results in different correlations: One

possibility is that assessing confidence only after the discrimination response might allow observers accumulate additional discrimination evidence (Kiani et al., 2014). As discrimination evidence implies negative correlations between stimulus quality and confidence in incorrect decisions, assessing confidence after the decision might miss a positive correlation between confidence and task accuracy at the time of the decision. A second possibility is that asking observers to report the orientation and their confidence at the same time induces a decision strategy no longer based on discrimination evidence, but on heuristics (Aitchison, Bang, Bahrami, & Latham, 2015). Again, a second experiment seems necessary to investigate if there results of Exp. 1 generalize to an experiment where observers reported their degree of confidence only after the orientation response.

Experiment 2

Material and methods

Participants. 39 participants (12 male, 27 female) took part in the experiment. The age of the participants ranged between 18 and 24 years ($M = 20.1$).

Trials structure. A trial in Exp. 2 was the same as in Exp. 1, except for the following difference (see Fig. 8). The mask was presented until participants gave a non-speeded discrimination response by key press whether the target had been horizontal or vertical. Only after the discrimination response, participants reported their confidence in being correct in the discrimination task. For this purpose, the question ‘how confident are you that your response was correct?’ was displayed on screen. Participants reported their confidence using one visual analog scale and again a joystick, meaning that participants selected a position along a continuous line between two end points by moving a cursor. The end points were labeled as ‘unsure’ and ‘sure’.

Fig 8. Trial structure of Exp. 2.

Results

Six participants were excluded from the analysis because their discrimination performance was not above chance level, BF_{10} 's $\leq .35$. For the 33 remaining participants,

discrimination performance ranged between chance level at an SOA of 8.3 ms ($M = 50.0\%$, $SD = 4.2$) and ceiling at the maximum SOA of 133.3 ms ($M = 95.3\%$, $SD = 5.5$). Confidence averaged 15.3% ($SD = 18.3$) of the width of the visual analog scale at an SOA of 8.3 ms and increased to a mean of 90.5% ($SD = 12.4$) at an SOA of 133.3 ms.

Correlation between SOA and confidence. As can be seen from the left panel of Fig. 9, confidence increased as a sigmoid function of SOA in correct trials. For incorrect trials, confidence increased in the range between 8.3 and 66.7, but then appears to have decreased at the final SOA of 133 ms. The average correlation coefficient was again large for correct trials, $M = .78$, $SD = .21$, and medium for incorrect trials, $M = .39$, $SD = .29$. A Bayesian analysis indicated decisive evidence that the average correlation coefficients were different from zero for correct trials, posterior of the mean 95% $CI = [.70 .85]$, $BF_{10} = 3.29 \cdot 10^{17}$, as well as incorrect trials, posterior of the mean 95% $CI = [.28 .49]$, $BF_{10} = 1.52 \cdot 10^6$. Given the apparent dip in confidence at the longest SOA, we decided post-hoc to perform a test if confidence indeed decreased between the SOAs of 66.7 and 133.0. However, the Bayes factor was not conclusive, posterior of the mean decrease in confidence between the two SOAs 95% $CI = [-.9 25.4]$, $BF_{10} = .84$.

Fig. 9. Mean confidence (left panel) and response time (right panel) depending on stimulus-onset-asynchrony (X-axis) and accuracy of the discrimination decision (different colors and symbols).

Correlation between SOA and reaction times. In Exp. 2, there was very strong evidence that correct responses were faster than incorrect ones, posterior of the mean difference $95\% CI = [69.4 \ 171.2]$, $BF_{10} = 1.0 \cdot 10^3$. As shown by the right panel of Fig. 8, correct responses also became faster with increasing SOA. The average correlation was weakly negative just as in Exp. 1, $M = -.17$, $SD = .20$; however, in Exp. 2, there was decisive evidence that the average correlation between SOA and reaction times was different from zero, posterior of the mean $95\% CI = [-.23 \ -.09]$, $BF_{10} = 635.5$. Just as in Exp. 1, response times to incorrect responses appeared to remain constant for shorter SOAs between 8.3 and 33.0, and to increase only for longer SOAs. However, the average correlation was negligibly small again, $M = .03$, $SD = .15$. The Bayesian analysis indicated that there was some evidence that the average correlation was zero, posterior of the mean $95\% CI = [-.02 \ .08]$, $BF_{10} = .25$.

Modeling analysis. As can be seen from the upper left and upper central panel of Fig. 10, the WEV-model, both the version with SOA-dependent variance of discrimination evidence as well as the version with constant variance provided good accounts of the data of Exp. 2, except that they appeared unable to reproduce confidence in incorrect trials at the maximum SOA of 133.3 ms.

Fig. 10. Mean confidence predicted by the seven models (in separate panels) depending on stimulus-onset-asynchrony (x-Axis) and accuracy of the discrimination response in Exp. 2. Straight lines indicate the prediction for correct trials, dotted lines for incorrect trials. Circles indicate observed confidence in correct trials, and triangles in incorrect trials. Error bars indicate 1 SEM.

The upper row of Fig. 11 again shows that the two flavors of the WEV- model performed best in reproducing the correlation between SOA and confidence on the level of each single participant. Nevertheless, it can also be seen that the majority of symbols is located to the right of the major diagonal, indicating that the two WEV-models tended to overestimate the correlation between SOA and confidence. The SDT model with SOA-dependent variance was the only alternative model that occasionally reproduced a positive correlation between SOA and confidence in incorrect trials, while all the other models incorrectly predicted negative correlations between SOA and confidence in incorrect decisions.

Fig. 11. Observed gamma correlation coefficients between SOA and confidence as a function of the predicted gamma correlation coefficient for the different models in separate panels in Exp. 2. Each symbol represents data from one participant. Error bars indicate the standard error of the correlation coefficient.

The WEV-models again were the two models that fitted the data best in terms of BIC and AIC_c: The best model overall was again the WEV-models with SOA-dependent variance

of discrimination evidence ($BIC: M = 1406; AIC_c: M = 1334$), followed by the weighted evidence and visibility model with constant variance; $BIC: M = 1410, AIC_c: M = 1342$. The best model that did not involve weighting of discrimination evidence and visibility was the SDT model with SOA-dependent variance, although the fit was decisively worse according to both metrics ($BIC: M = 1422; AIC_c: M = 1359$). All the other models performed even worse (all BIC 's: $M \geq 1529$; all AIC_c 's: $M \geq 1466$).

Just as in Exp. 1, the Bayes factors analysis revealed some evidence against a difference in model fit between the WEV-model with SOA-dependent variance and the WEV-model with constant variance, although in Exp. 2, the result regarding the AIC_c was not conclusive:

- BIC : posterior of the mean ΔBIC : 95% $CI = [-13.6 \ 5.5]$, $BF_{10} = .20$
- AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-17.5 \ 1.5]$, $BF_{10} = .55$.

Concerning the other models, the Bayes factors provided evidence that the WEV-model with SOA-dependent variance fit the data better than each of the other five models:

- the SDT model with SOA-dependent variance:
  - BIC : posterior of the mean ΔBIC : 95% $CI = [-26.6 \ -4.8]$, $BF_{10} = 6.3$
  - AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-34.9 \ -12.8]$, $BF_{10} = 287.2$
- the SDT rating model:
  - BIC : posterior of the mean ΔBIC : 95% $CI = [-161.3 \ -82.4]$, $BF_{10} = 6.4 \cdot 10^4$
  - AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-173.9 \ -95.2]$, $BF_{10} = 3.7 \cdot 10^5$
- the postdecisional accumulation model:
  - BIC : posterior of the mean ΔBIC : 95% $CI = [-160.7 \ -79.6]$, $BF_{10} = 3.0 \cdot 10^4$
  - AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-168.9 \ -87.6]$, $BF_{10} = 9.4 \cdot 10^4$
- the noisy SDT model:

- 673   – BIC : posterior of the mean ΔBIC : 95% $CI = [-168.2 -88.6]$, $BF_{10} = 1.4 \cdot 10^5$
- 674   – AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-176.3 -96.7]$, $BF_{10} = 4.5 \cdot 10^5$
- 675   • the two channel model:
- 676   – BIC : posterior of the mean ΔBIC : 95% $CI = [-168.9 -85.2]$, $BF_{10} = 5.2 \cdot 10^4$
- 677   – AIC_c : posterior of the mean ΔAIC_c : 95% $CI = [-177.6 -93.8]$, $BF_{10} = 1.6 \cdot 10^5$.

678 Discussion

679   Exp. 2 suggested that the WEV-model with SOA-dependent variance of
 680 discrimination evidence provides a better account for confidence in masked orientation
 681 discrimination decision than the SOA-dependent SDT model, the SDT rating model, the
 682 noisy SDT model, the postdecisional accumulation model, the two channel model even when
 683 confidence was recorded after orientation responses. Moreover, there was again very strong
 684 evidence that longer SOAs increased confidence both in correct as well as incorrect trials.
 685 Positive correlations between SOA and confidence in incorrect decisions were reproduced in
 686 principle by the WEV-model and the SOA-dependent SDT model, although only the first one
 687 accounted reasonably well for confidence as a function of SOA. Concerning response times,
 688 SOAs speeded up response times in correct trials only, whereas in incorrect trials, there
 689 seemed to be no relation between response times and SOA.

690   Models based on response times are not able to explain the positive correlation
 691 between SOA and confidence in incorrect trials observed in Exp. 2. The reason is that there
 692 was evidence against a correlation between SOA and confidence in incorrect trials. If
 693 participants had learnt to associate longer decision times with a lower probability of being
 694 correct (Kiani et al., 2014), then participants' confidence should have been particularly low in
 695 incorrect responses at SOAs of 66.7 and 133.3 ms, because these were the slowest responses
 696 in Exp. 2. However, the minimal mean confidence occurred at an SOA of 16.7 ms

independent of whether the decision was correct or not. It should be noted that the present study does not imply that there is no effect of decision time on confidence. What the present experiment does imply is that if there had been an effect of decision time on confidence, the effect would not explain the observed correlation between SOA and confidence in incorrect decisions in the present study.

Why is confidence in errors positively correlated with SOA in the present study, although previous studies observed a negative correlation between confidence in errors and stimulus quality (Moran et al., 2015; Sanders et al., 2016)? As virtually the same pattern of results occurred in Exp. 1 and Exp. 2 despite the fact that confidence and decisions were recorded simultaneously in Exp. 1 and decision before confidence in Exp. 2, sequential or simultaneous assessment of responses and confidence cannot explain the differences between studies (Kiani et al., 2014; Sanders et al., 2016). It might be speculated that some stimuli provide cues to the quality of the stimulation independent of the discrimination evidence while discrimination evidence and cues to the quality of the stimulation are identical in other stimuli. When no cues to the quality of the stimulation are available, models based on discrimination evidence alone might be sufficient to describe confidence. Only when percept is informative about the quality of stimulation independent of the discrimination evidence, the WEV-model might outperform the SDT model in explaining confidence. Future studies are necessary to test this hypothesis.

The apparent “dip” in confidence at the maximum SOA of 133.3 ms is an unresolved issue in Exp. 2: While the WEV model predicts that confidence monotonically increases with SOA, in Exp. 2, confidence seemed to switch from increasing to decreasing for the maximum SOA. As the statistical analysis of the dip was not conclusive, we would probably disregard the last data point as unreliable due to the low number of errors at the maximum SOA if we had not observed an identical dip during pilot experiments. A potential explanation for the

722 sudden decrease in confidence would be detection of motor errors. Given observers had
723 detected they accidentally pressed the wrong button, they should have reported a minimal
724 degree of confidence. However, confidence in incorrect decisions is challenging to measure
725 at high SOAs because participants hardly make any errors at these SOAs. Future studies
726 appear necessary to investigate if the WEV-model needs to be extended to encompass error
727 detection to account for confidence in masked discrimination decisions.

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the subjective probability of being correct (Sanders et al., 2016), heuristic inference may be expected to be used in confidence in discrimination decisions as well.

However, whether the WEV-model constitutes an example of heuristic inference or not depends on the specific concept of heuristic inference. In the context of theories about confidence, previous authors are not entirely consistent in what calculations underlying confidence qualify as heuristic inference. First, in a task where two features of the stimulus determined the difficulty of the decision conjointly, heuristics were argued to depend only on single features of the stimulus, in opposition to calculations of confidence where the two features of the stimulus were combined (Barthelmé & Mamassian, 2010). Others stated that according to heuristic theories, confidence is not calculated from discrimination evidence extracted during the decision process (Moran et al., 2015). Finally, contrasting the Bayesian with the heuristic approach, it was argued that all transformations of the sensory input quality as heuristic except when the probability of being correct is explicitly calculated (Aitchison et al., 2015). The WEV model shares some, but not all purported characteristics heuristic inference: Consistent with heuristic inference, the WEV model does not involve explicit calculations of the probability of being correct, and confidence is not exclusively based on discrimination evidence. However, in contrast to what heuristic inference is often described, discrimination evidence does inform confidence in the WEV-model. Crucially, the WEV model does not involve a simplification as discrimination evidence is assumed to be combined with, not replaced by the visibility of the stimulus. Overall, irrespective of which is most suitable concept of heuristic inference in the context of decision confidence, it is necessary to stress that the WEV model combines purported features of heuristic and computational theories.

Confidence: Informed by many signals

While a combination of discrimination evidence and stimulus visibility appears sufficient to explain confidence in the present study, there is converging evidence that confidence in visual discrimination decisions is determined by many cues.

A mechanism similar to one described in the present study relies on the variability of discrimination evidence provided by the stimulation: When observers discriminated the average color of an array of colored shapes, confidence was not only determined by the distance of the average color to the category boundary, but was also affected by the variability of color across the array (Boldt, de Gardelle, & Yeung, 2017). Moreover, in a global motion discrimination task, confidence depended on the consistency of motion signals, although discrimination performance was equated (Spence, Dux, & Arnold, 2015). A second mechanism may be based on monitoring the time required to reach a decision. Although there was no evidence for such a mechanism in the present study, a previous study manipulated the time needed to reach the decision in a global motion discrimination task while equating task performance, observing that decision time directly informs confidence (Kiani et al., 2014). Finally, there is robust evidence that observers are able to occasionally detect their own errors (Yeung & Summerfield, 2012). Based on SDT or WEV-model, it would not be possible to change one's mind about which response is the correct one, which is why there must be an additional mechanism to explain error detection. Previous studies argued that the accumulation of evidence for the responses continues even after the decision is made, which could account for the detection of errors (Van Den Berg et al., 2016; Yeung & Summerfield, 2012). In Exp. 2, there was some indication that error detection might have played a role at the maximum SOA, although the data was not conclusive here.

Overall, it is tempting to speculate about a common mechanism underlying these effects: A metacognitive system may calculate confidence based on as many cues to the probability of being correct as available in a specific task. Visibility of the stimulus, variance

of colors, variability of motion signals, elapsed decision time, and detected errors may all be cues to that system. Consistent with a shared metacognitive system, confidence and error detection share one electrophysiological marker, the Pe component (Boldt & Yeung, 2015). However, more research appears necessary to investigate if there is a common mechanism underlying confidence in these tasks.

Dynamics of decisions and confidence

While the WEV model provides a reasonable account for decisions and confidence in a masked orientation task, it would be even more satisfying to have one model to explain not only decision and confidence, but also decision times at the same time. However, the WEV-model was not designed to account for response times. Several previous studies attempted to provide such a unified account (Kiani et al., 2014; Moran et al., 2015; Pleskac & Busemeyer, 2010), but these theories are not consistent with the present data: The bounded accumulation model cannot explain the way how the pattern of response times as a function of SOA was inconsistent with the pattern of confidence. Postdecisional accumulation models predict a negative correlation between SOA and confidence in incorrect trials and are thus not in accordance with the present data as well.

Although this was not the focus of the present study, future studies might be able to provide an extension of the WEV-model in the temporal domain. While sequential sampling processes are natural candidates to account for the dynamics of evidence (Ratcliff et al., 2016), to our knowledge no study has investigated the temporal dynamics of other cues to being correct besides the discrimination evidence. Such a dynamical extension of the WEV model should be able to account for decisions, confidence, and decision time in masked orientation decisions at the same time.

824 Summary

825   The best explanation for confidence in masked orientation decisions is the WEV-
826 model, which argues that confidence is calculated from discrimination evidence as well as the
827 visibility of the stimulus. Signal detection models, post-decisional accumulation models, two
828 channel models, and decision-time based models are all not able to explain the pattern of
829 confidence in incorrect decisions as a function of SOA. We suggest that the metacognitive
830 system is able to calculate one's confidence by combining multiple cues about being correct
831 in visual discrimination decisions.

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Appendix

The WEV-model with SOA-dependent variance of discrimination evidence

The WEV-model with SOA-dependent variance of discrimination evidence is described first here, because it represents a general case that incorporates the SDT model, the SDT model with SOA-dependent variance, the noisy SDT model, and the WEV model with constant variance as special cases. The difference to the other models is explained below.

According to the WEV-model with SOA-dependent variance of discrimination evidence, in each trial of the experiment, the presentation of the stimulus $S \in \{0,1\}$ provides the observer with a sample of discrimination evidence x to select a response $R \in \{0,1\}$. Participants are assumed to respond $R = 0$, when $x < \theta$, and $R = 1$ if $x > \theta$. θ is a free parameter that represents the decision criterion. x is modeled as a random sample from a Gaussian distribution f :

$$x \sim f_{\mu_x, s^2} \quad (\text{A1})$$

The mean μ_x and variance s^2 of f are calculated as

$$\mu_x = (S - 0.5) \times d_m \quad (\text{A2})$$

$$s^2 = 1 + k \times d_m^2 \quad (\text{A3})$$

Thus, $s^2 = 1$ when $d_m = 0$, and the increase with d_m^2 is proportional to the parameter k for $d_m > 0$.

The decision variable y , which is evaluated when observers select one out of n confidence categories $C \in \{1, 2, \dots, n\}$, is again modelled as a random sample out of a Gaussian distribution:

$$y \sim f_{\mu_y, \sigma} \quad (\text{A4})$$

1003 Its variance σ^2 represents imperfect access to the evidence underlying the decision as
 1004 well as in case of the WEV-models imperfect estimation of the quality of the stimulation.
 1005 According to the WEV-models, the mean of the decision variable y is given as

$$\mu_y = (1 - w) \times x + w \times (2R - 1) \times (d_m - \text{mean}(d)) \quad (\text{A5})$$

1006 In this formula, w represents the relative weight observers put on visibility and
 1007 sensory evidence for confidence.

1008 Participants are assumed to report a minimal degree of confidence $C = 1$ about the
 1009 response $R = 0$ when $y > c_{01}$, and about a response $R = 1$ when $y < c_{11}$. The probability
 1010 of a response $R = 0$ and confidence $C = 1$ can be calculated as:

$$P(R = 0 \wedge C = 1) = P(x < \theta) \times P(y > c_{01} | x) \quad (\text{A6})$$

$$= \int_{-\infty}^{\theta} f_{\mu_x, \sigma^2}(x) \times \left(\int_{c_{01}}^{\infty} f_{\mu_y, \sigma^2} dy \right) dx \quad (\text{A7})$$

1011 The probability of a response $R = 1$ and confidence $C = 1$ is calculated analogously:

$$P(R = 1 \wedge C = 1) = \int_{\theta}^{\infty} f_{\mu_x, \sigma^2}(x) \times \left(\int_{-\infty}^{c_{11}} f_{\mu_y, \sigma^2} dy \right) dx \quad (\text{A8})$$

1012 Participants report a medium degree of confidence $C = i$ given $R = 0$ if $c_{0(i+1)} <$
 1013 $y < c_{0i}$, and likewise, a medium degree of confidence $C = i$ given $R = 1$ if $c_{1i} < y <$
 1014 $c_{1(i+1)}$. The probability of confidence $C = i$ is given by:

$$P(R = 0 \wedge C = i) = \int_{-\infty}^{\theta} f_{\mu_x, \sigma^2}(x) \times \left(\int_{c_{0(i+1)}}^{c_{0i}} f_{\mu_y, \sigma^2} dy \right) dx \quad (\text{A9})$$

$$P(R = 1 \wedge C = i) = \int_{\theta}^{\infty} f_{\mu_x, s^2}(x) \times \left(\int_{c_{1i}}^{c_{1(i+1)}} f_{\mu_y, \sigma^2} dy \right) dx \quad (\text{A10})$$

1015 Finally, observers report a maximum degree of confidence $C = n$ about the response
 1016 $R = 0$ when $y < c_{0(n-1)}$, and about the response $R = 1$ when $y > c_{1(n-1)}$. Therefore, the
 1017 probability of confidence given $C = n$ is given by:

$$P(R = 0 \wedge C = n) = \int_{-\infty}^{\theta} f_{\mu_x, s^2}(x) \times \left(\int_{-\infty}^{c_{0(n-1)}} f_{\mu_y, \sigma^2} dy \right) dx \quad (\text{A11})$$

$$P(R = 1 \wedge C = n) = \int_{\theta}^{\infty} f_{\mu_x, s^2}(x) \times \left(\int_{c_{1(n-1)}}^{\infty} f_{\mu_y, \sigma^2} dy \right) dx \quad (\text{A12})$$

1018 The WEV-model

1019 The WEV-model is identical to the WEV-model with SOA-dependent variance,
 1020 except that k is fixed at 0. Thus, in the WEV-model, (A3) is reduced to $s^2 = 1$.

1021 The noisy SDT model

1022 The noisy SDT model is identical to the WEV-model with SOA-dependent variance,
 1023 except that the parameters k and w are fixed at 0. Therefore, according to the noisy SDT
 1024 model, (A3) is reduced to $s^2 = 1$, and (A5) to $\mu_y = x$.

1025 The SDT model with SOA-dependent variance

1026 According to the SDT model with SOA-dependent variance, the parameters σ and w
 1027 are fixed at 0. At a result, the formulae (A7) and (A12) can be reduced to

$$P(R = 0 \wedge C = 1) = \int_{c_{01}}^{\theta} f_{\mu_x, s^2}(x) dx \quad (\text{A13})$$

$$P(R = 1 \wedge C = 1) = \int_{\theta}^{c_{11}} f_{\mu_x, s^2} dx \quad (\text{A14})$$

$$P(R = 0 \wedge C = i) = \int_{c_{0(i+1)}}^{c_{0i}} f_{\mu_x, s^2}(x) dx \quad (\text{A15})$$

$$P(R = 1 \wedge C = i) = \int_{c_{1i}}^{c_{1(i+1)}} f_{\mu_x, s^2} dx \quad (\text{A16})$$

$$P(R = 0 \wedge C = n) = \int_{-\infty}^{c_{0(n-1)}} f_{\mu_x, s^2}(x) dx \quad (\text{A17})$$

$$P(R = 1 \wedge C = n) = \int_{c_{1(n+1)}}^{\infty} f_{\mu_x, s^2} dx \quad (\text{A18})$$

1028   **The SDT model**

1029   According to the SDT, not only are the parameters σ and w are fixed at 0, k is 0 as
 1030 well. At a result, the formulae (A13) - (A18) apply, except that s^2 is always equal to 1.

1031   **The postdecisional accumulation model**

1032   According to the postdecisional accumulation model, k is again fixed at 0. The
 1033 formulae (A7) - (A12) apply. However, μ_y is calculated in a different way than in the WEV-
 1034 model:

$$\mu_y = x + (2S - 1) \times d_i \times b \quad (\text{A19})$$

1035   The free parameter b represents the amount of postdecisional accumulation expressed
 1036 in terms of the sensitivity without postdecisional accumulation. Moreover, σ^2 is not a free
 1037 parameter as in the two WEV-models or the noisy SDT model, but is always equal to b .

1038   **The dual channel model**

1039   According to the dual channel, k is again fixed at 0. The formulae (A7) - (A12) apply,
 1040 except that σ^2 is not a free parameter as in the two WEV-models or the noisy SDT model,
 1041 but is fixed at 1. Moreover, μ_y is calculated in a different way than in the WEV-model:

$$\mu_y = a \times d_i \quad (\text{A20})$$

1042