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Perceptual learning effect on decision and confidence thresholds

Guillermo Solovey [a,b,f,*], Diego Shalom [a,d,f], Verónica Pérez-Schuster [a,d,e,f], Mariano Sigman [a,c,d,f]

[a] Laboratorio de Neurociencia Integrativa, Buenos Aires, Argentina
[b] Instituto de Cálculo, Facultad de Ciencias Exactas y Naturales, Universidad de Buenos Aires, Argentina
[c] Laboratorio de Neurociencia, Universidad Torcuato di Tella, Buenos Aires, Argentina
[d] Departamento de Física-IFIBA, Facultad de Ciencias Exactas y Naturales, Universidad de Buenos Aires, Argentina
[e] Laboratorio de Neurobiología de la Memoria, Departamento Fisiología, Biología Molecular y Celular, FCEyN, UBA and IFIBYNE-CONICET, Buenos Aires, Argentina.
[f] CONICET, Argentina

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A B S T R A C T

Practice can enhance of perceptual sensitivity, a well-known phenomenon called perceptual learning. However, the effect of practice on subjective perception has received little attention. We approach this problem from a visual psychophysics and computational modeling perspective. In a sequence of visual search experiments, subjects significantly increased the ability to detect a "trained target". Before and after training, subjects performed two psychophysical protocols that parametrically vary the visibility of the "trained target": an attentional blink and a visual masking task. We found that confidence increased after learning only in the attentional blink task. Despite large differences in some observables and task settings, we identify common mechanisms for decision-making and confidence. Specifically, our behavioral results and computational model suggest that perceptual ability is independent of processing time, indicating that changes in early cortical representations are effective, and learning changes decision criteria to convey choice and confidence.

1. Introduction

Perceptual ability improves with practice, a well studied phenomenon known as perceptual learning (Goldstone, 1998; Kawato et al., 2014; Watanabe & Sasaki, 2015). Most studies in perceptual learning focus on objective visual perception, i.e. changes in task performance. However, the ability to discriminate visual stimuli is only the *objective* side of visual perception; every perceptual decision is also associated with subjective aspects, such as confidence. Although confidence and accuracy usually correlate, recent findings suggest that in some conditions the two may dissociate (Del Cul, Dehaene, Reyes, Bravo, & Slachevsky, 2009; Graziano & Sigman, 2009; Lau & Passingham, 2006, 2007; Rounis, Maniscalco, Rothwell, Passingham, & Lau, 2010; Zylberberg, Roelfsema, & Sigman, 2014). Moreover, it has long been suggested that confidence is related to subjective awareness (Peirce & Jastrow, 1884) whereas accuracy may only reflect processing capacity (Lau, 2008). Therefore, in order to create a complete picture of perceptual learning, it is important to understand the effect of

* Corresponding author at: Instituto de Cálculo, Facultad de Ciencias Exactas y Naturales, Universidad de Buenos Aires, Argentina.
E-mail address: gsolovey@gmail.com (G. Solovey).

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practice on both visual discrimination performance and subjective confidence. Reciprocally, perceptual learning may be a good experimental vehicle to understand dissociations between choice and confidence in perceptual decisions.

Several studies have shown that subliminal and unattended presentation of stimuli can lead to learning when paired in time with an attention-capturing visible stimulus (Seitz, Lefebvre, Watanabe, & Jolicoeur, 2005; Seitz & Watanabe, 2003, 2005). However, the converse has been much less explored. How does learning affect subjective experience? Are subjective aspects of vision affected in the same way as objective performance? One notable exception is the study by Schwiedrzik, Singer, and Melloni (2011) in which subjects trained on a perceptual task improved sensitivity and subjective awareness on the *same* task for which they were trained. It remains unclear whether learning to identify a shape transfers to a *different* task setting and, whether objective and subjective aspects of perception share the same underlying mechanisms. Can practice in a visual discrimination task change confidence thresholds? Or, alternatively, changes in confidence are explained merely by an increase in signal strength? In this work, we designed an experiment to distinguish between these two alternatives. By measuring simultaneously confidence and choice in different tasks during an extensive learning period, we seek to understand the specific underlying mechanisms of practice on objective and subjective learning.

Our experiment is divided in three phases. During the learning phase, subjects were extensively trained in a visual search task, which involves identifying a shape among distractors (Sigman & Gilbert, 2000). Before and after training, subjects performed two well known protocols which parametrically vary the visibility of the trained target: the attentional blink task (Raymond, Shapiro, & Arnell, 1992) and a visual masking task (Breitmeyer, 1984; Enns & Di Lollo, 2000). Given that practice improves the ability to identify a trained shape, we empirically tested if this ability is transferred to a different task in which subjects need to detect the same target shape. In addition, we measured the specific effect of learning on confidence. Our main aim in this study is to compare the ability of different classes of signal detection theoretic models to account for the data and identify which aspects of the decision making process change with learning and whether those changes vary or not across tasks.

2. Materials and methods

2.1. Subjects and experimental design

A total of 7 subjects participated in this study (4 males, age 24.9 ± 2.1). All subjects gave written informed consent, were naïve about the aims of the experiment and reported normal or corrected-to-normal vision. Subjects performed several sessions of psychophysical tasks, as illustrated in Fig. 1A. Each session was performed on a different day. The sequence started with one session of the attentional blink (AB) task and one session of the visual masking (VM) task. Then, subjects entered the learning phase that consisted of several sessions of the same visual search task. Finally, subjects repeated one session of the AB and one session of VM tasks. One subject did not perform the AB task; he/she only completed the VM tasks, once before and once after the learning phase.

2.2. Stimuli

Visual stimuli were presented on a 19 in. monitor (Samsung Syncmaster 998 MB) at a viewing distance of 75 cm. Stimuli in all experiments were black on a uniform gray background.

2.3. Visual search task

Each trial consisted of a 1500 ms cycle, as illustrated in Fig. 1B. A 5×5 array consisting of a central fixation cross and 24 shapes in the remaining locations was presented for 200 ms. The array subtended $10.9° \times 10.9°$. During the subsequent 1300 ms inter-stimulus interval, the subject had to report whether or not a target shape was present by pressing the appropriate key on a computer keyboard. Each participant was trained to find a triangle of a certain orientation among an array of distractors (triangles of other orientations). Target and distractors were equilateral triangles on four different orientations (up, down, left, right) and 1.6° in size. On "target present" trials, the trained stimulus appeared in one randomly selected location within the array. In 20% of the trials the target was absent. Each session consisted of 8 blocks of 150 trials. Subjects performed training sessions until the percentage of correct responses within a session achieved 85%. Five subjects did 6 training sessions and two did 7 sessions. Three subjects were trained for left-, two for down-, and two for right-oriented triangles. Screen resolution was set to 1024×768 and the refresh rate, 85 Hz.

2.4. Attentional blink task

Each trial consisted on a rapid serial visual presentation of 18 stimuli, each one presented for 100 ms (Fig. 1C). The sequence started with 4–6 distractors followed by the first target (T1), a banana-shaped outline. A variable number of distractors (ND, from 0 to 7) separated T1 from the second target (T2), an equilateral triangle of the same shape and the same possible orientations as the triangles in the visual search task. Finally, enough distractors were added to complete

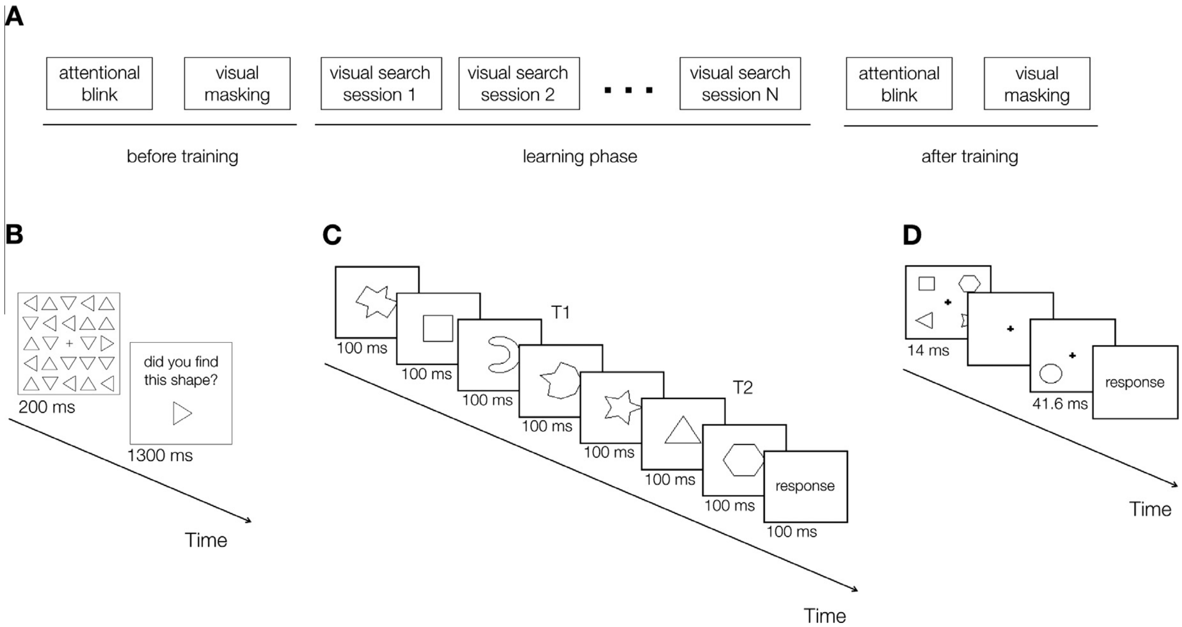

Fig. 1. Task design. A: Experimental design: Subjects performed a sequence of psychophysical tasks (from left to right in the figure). Training in visual search was used to enhance subjects' ability to detect the target shape (a triangle). The number of training sessions was N = 6 for 5 subjects and N = 7 for two subjects (necessary to reach 85% correct responses). Before and after the learning phase, subjects performed an attentional blink and a visual masking task, in random order. In both tasks, subjects had to provide an objective report (whether or not they saw the target triangle) and a subjective measure such as confidence in their own decision (see Section 2 for details). B: Visual search task used in the learning phase: each trial consisted of a 1500 ms cycle. In the first 200 ms, we presented a 5×5 array consisting of a central fixation cross and 24 shapes in the remaining locations; subjects' response was recorded during the subsequent 1300 ms inter-stimulus interval. Target present stimuli arrays were presented on 80% of the trials and consisted of a triangle in the trained orientation and 23 triangles randomly oriented in the other orientations. C: Attentional Blink task: A rapid sequence of geometrical shapes is presented, including two targets, a banana-shape (T1) and a triangle (T2). D: Visual masking task: The stimulus consisted of 4 shapes, one of which was a triangle. A mask was presented after (forward masking, as in the figure) or before the stimulus (backward masking).

18 stimuli. The time between presentation of T1 and T2 (stimulus onset asynchrony, SOA) is $100 \times (\text{ND} + 1)$ ms. T2 was present on 80% of the trials. Distractors were pulled randomly from a group of geometrical outlined shapes (square, rhomboid, pentagon, hexagon, 4- and 5-corner stars, and some irregular shapes, some of which are shown in Fig. 1C). All targets and distractors were 0.9° in size, presented on the center of the screen using a resolution of 800×600 at 144 Hz refresh rate.

After the presentation of the sequence of stimuli, subjects had to report the orientation of T1 in a four choice discrimination task followed by a subjective report of the visibility of T2 on a scale from 0 -when they did not see any triangle- to 100 -when they saw a triangle- using a sliding bar at the center of the screen. The third response was a four choice discrimination task on the orientation of T2. Finally subjects reported confidence on their own response about T2 orientation, on a scale from 0 to 100. All responses were given using a computer mouse. Each participant completed two blocks of 180 trials. As usual in this task, we discarded from further analysis trials in which the orientation of T1 was incorrectly identified. Although visibility ratings were collected, for the purpose of this manuscript we will only analyze confidence reports. Each participant completed three blocks of 180 trials.

2.5. Visual Masking task

In visual masking trials, subjects had to identify a target (an equilateral triangle of the same shape and possible orientation as in the perceptual learning task) presented briefly (14 ms) in one corner of a square (Fig. 1D). The three other corners contained distractors of the same geometrical shapes used as distractors in the AB experiment. The shapes were 0.5° in size located in the corners of a screen-centered square of 10.5° in size. A mask consisting of a circle surrounding the target (mask) was presented at a variable time after or before the presentation of the stimuli. The circle was 0.7° in diameter and 0.1° line width, and was presented for 41.6 ms. The time between presentation of the stimuli and the mask (the duration of the blank screen) is referred as inter-stimulus interval (ISI). ISI values were [−20.8; −6.9; 6.9; 20.8; 34.7; 48.6; 69.4; 111] ms. Positive ISI values indicate that the mask was presented after the stimulus containing the target (a condition called backward masking) and negative ISI values correspond to the mask presented before the stimulus screen (forward masking). The target was present on 80% of the trials. The remaining trials did not contain the target and the masked quadrant was left empty. In target-present trials, the location of the target was randomly selected among the four possible locations. Subjects did not know the location of the target at no moment (neither before its presentation nor after reporting its orientation). For this task, we used a screen resolution of 800 × 600 and 144 Hz refresh rate.

Following stimuli presentation, subjects reported the orientation of the target triangle in a four choice discrimination task and then their confidence on the orientation response in a scale from 0 -when they were just guessing- to 100 -when they were completely certain-. Finally subjects responded the visibility of the target, on a scale from 0 -when they couldn't detect anything behind the mask- to 100 -when they saw something behind the mask, even if they couldn't detect the shape of the target. All responses were reported using a computer mouse. Each participant completed three blocks of 180 trials.

2.6. Signal detection theoretic models

We model behavioral data from the AB and VM tasks using computational models within the framework of Signal Detection Theory (SDT). The goal of the models is to identify what aspects of the perceptual decisions were affected by learning. To this end, a first approximation of the models is that the stimulus presented on each trial belongs to one of two classes: S_1 (when any untrained target is present), S_2 (when the trained target is present). When the stimulus is S_1, the model assumes that an internal response x is drawn in the brain of the observer with a Gaussian probability distribution (Fig. 2). Similarly, x follows a different Gaussian distribution when the stimulus is S_2 (Fig. 2). On every trial, according to the model, a binary decision is made comparing x with a criterion such that if $x > x_c$ the subject response is "trained target present"; otherwise, the response is "an untrained target is present". Confidence reports are generated comparing x with additional confidence thresholds. Finally, the models assume that criteria for choice response and confidence reports were set in the same way for each SOA/ISI.

In our experiments, subjects reported confidence in a continuous scale from 0 to 100 using a computer mouse. In principle, subjects would use the whole scale. However, in practice confidence was at floor (0) or ceiling (100) in most trials. Therefore, for modeling purposes, we discretize confidence such that confidence is 1 (when the subject report is 0), 2 (when it is larger than 0 and below 100) and 3 (when it is equal to 100, complete certainty). As shown in Fig. 2, confidence is 1 (min), 2 or 3 (max).

Without loss of generality, the variance of the "untrained target" distribution is 1. The variance of the "trained target" distribution, σ_T, is equal to 1 before training, but may potentially change with training. Therefore some of the models we tested consider σ_T as an additional free parameter.

We assume that μ depends on the task parameters (SOA or ISI) but the variance is an internal property of the subject perceptual system. In general, learning could affect all parameters of the distributions: μ, σ_T and the decision and confidence thresholds. However, we considered seven models that differ on the effect of learning on the distributions of the internal responses:

Model 1: in this model learning only changes μ and the effect of learning is independent of SOA/ISI.
Model 2: same as model 1 except that learning can also affect σ_T.
Model 3: in this model learning only changes the internal noise σ_T.
Model 4: learning changes μ independently for each SOA/ISI.
Model 5: this model, as well as models 6 and 7, considers that learning can change the decision and confidence criteria. Also, learning changes μ by a constant amount.
Model 6: same as model 5 but learning affects μ independently of SOA/ISI.
Model 7: same as model 6 but learning can also affect σ_T.

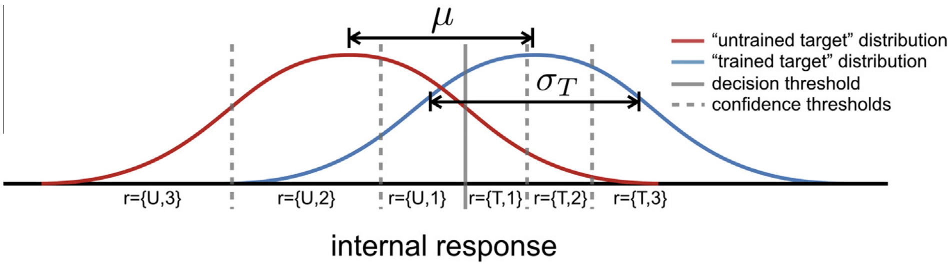

Fig. 2. Schematic illustration of the signal detection theoretic models: The red curve represents the internal response distribution when the trained target is present and the blue curve shows the distribution when any untrained target is present. The subject response on one trial is the "trained target" when the internal response is larger than the decision threshold (vertical solid line). The dashed vertical lines represent confidence thresholds. In this example there are two confidence thresholds resulting in three confidence levels (1, 2, 3). If the internal response is larger than the decision threshold, the possible responses are {T, 1}, {T, 2}, {T, 3} according to the confidence level, as indicated in the x-axis. We considered 7 different models that differ in the effect of training on the distributions of the internal response, whether it changes the distance between the distributions (μ), the variance of the trained target distribution (σ_T) and/or the thresholds (see Table 1 for details). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Parameters of the signal theoretic detection models (illustrated in Fig. 8). The models differ in the effect of training on the parameters of the signal distributions. In all models, μ_i is the distance between the mean values of the distributions (different for each SOA or ISI) and σ_T is the standard deviation of the trained orientation internal response distribution. The number of parameters differs between the AB and VM tasks because there were 9 different SOA values in AB and 8 ISI in the VM task.

Model	Parameters	Number of parameters ab|masking	Effect of training
1	μ_i dμ thresholds	15|14	μ_i(after) = μ_i(before) + dμ
2	μ_i dμ thresholds σ_T(after)	16|15	μ_i(after) = μ_i(before) + dμ σ_T(after) $\neq$1
3	μ_i thresholds σ_T(after)	15|14	σ_T(after) $\neq$1
4	μ_i(before) μ_i(after) thresholds	23|21	μ_i(after) $\neq$ μ_i(before)
5	μ_i dμ thresholds(before) thresholds(after)	20|19	μ_i(after) = μ_i(before) + dμ thresholds(after) thresholds (before)
6	μ_i(before) μ_i(after) thresholds(before) thresholds(after)	28|26	μ_i(after) $\neq$ μ_i(before) thresholds(after) $\neq$ thresholds (before)
7	μ_i(before) μ_i(after) thresholds(before) thresholds(after) σ_T(after)	29|27	μ_i(after) $\neq$ μ_i(before) thresholds(after) $\neq$ thresholds (before) σ_T(after) $\neq$1

Table 1 summarizes the parameters and the effect of learning for each of the models. The number of parameters to estimate varies from 14 to 29 depending on the model. This may seem to be a very large number of parameters, but it should be compared with the size of the subject response space. Each subject is characterized by a set of numbers indicating the number of responses on each of the following categories: before/after training (2), trained/untrained stimulus (2), SOA/ISI (9, 8) values, choice response (2: trained/untrained), confidence (3: low/med/high). The total number of response categories is 192 for the visual masking task and 216 for the attentional blink task. We have considered a different mapping of confidence reports: a 5 points discretization with bottom, middle and top percentile for each subject (for those trials in which confidence was not at floor nor ceiling). However, despite having more free parameters, the net increase in fitting quality was negligible. Therefore, we decided to report only the seven models described above in which confidence was discretized in 3 levels.

2.7. Model fitting

We fit the models to behavioral data using a maximum likelihood estimation approach that has previously been used within a signal detection framework (Dorfman & Alf, 1969). Briefly, the likelihood of a set of signal detection model parameters given the observed data can be calculated using the multinomial model. Formally,

$$L(\theta|data) \propto \prod_{i,j} P_\theta(R_i|S_j)^{n_{data}(R_i|S_j)},$$

where each R_i is a behavioral response a subject may produce on a given trial, and each S_j is a type of stimulus that may be shown on that trial. The expression "$n_{data}(R_i|S_j)$" is a count of how many times a subject actually produced R_i after being shown S_j. The expression "$P_\theta(R_i|S_j)$" denotes the probability with which the subject produces the response R_i after being presented with S_j, according to the signal detection model specified with parameters θ.

Note that the models were not fit to summary statistics of performance such as percent correct. Rather, models were fit to the full distribution of probabilities of each response type contingent on each stimulus type. Various kinds of summary statistics (*e.g.* d′, percent correct and so on) can be derived from this full behavioral profile of stimulus-contingent response probabilities.

We fitted all models under consideration by finding the maximum likelihood parameter values θ. Maximum likelihood fits were found using a simulated annealing procedure (Kirkpatrick, Gelatt, & Vecchi, 1983). Model fitting was conducted separately for each subject's data. The estimation procedure was reliable; subsequent repetitions of the model fitting procedure produced negligible variations in the parameter estimates for each model of each subject's data.

2.8. Formal model comparison

The maximum likelihood associated with each model characterizes how well that model captures patterns in the empirical data. In principle, the model with more free parameters has a greater chance of accounting for the data. However, comparing models directly in terms of likelihood can be misleading; greater model complexity can allow for tighter fits to the data but can also lead to undesirable levels of over-fitting, i.e., the erroneous modeling of random variation in the data. Therefore, we compared the models using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). This measure provides a means for comparing models on the basis of their maximum likelihood fits to the data while correcting for model complexity (in this case the number of parameters).

2.9. Signal detection measures

We estimate sensitivity (d') with the standard signal detection theoretic formula $d' = z(HR) - z(FA)$, where HR is the hit rate (rate of correct responses on 'target present' trials) and FAR the false positive rate. By false positive response we mean any trial in which the stimulus is any untrained target and the response of the subject is "trained target". The z transformation converts these rates to a z score (i.e., to standard deviation units).

3. Results

The experimental design and tasks are described in Fig. 1. Subjects were trained to identify a target shape during several sessions of a visual search task. Before and after training, subjects performed two classical visual tasks that parametrically vary the visibility of a target, the attentional blink and a visual masking task. The attentional blink is a phenomenon observed when stimuli are presented in a single location at a rate of 6–20 ms. A second target (T2) is often missed if presented between 180 and 400 ms after the first one (T1). The trademark of the AB is a U-shaped curve of T2 identification performance as a function of the time between the presentation of T1 and T2 (SOA). In the visual masking, the trained target and three distractors were presented briefly (14 ms) in the corners of a square. A visual mask was presented after or before the presentation of the stimuli (inter-stimulus interval, ISI). Target visibility depends on the ISI and it usually follows a U-shaped function.

3.1. Perceptual learning: visual search performance increases with practice

On day 1, we collected baseline information of detection performance and subjective confidence on the attentional blink (AB) and visual masking (VM) tasks. The target shape on both tasks was a triangle oriented up, down, left or right (see Fig. 1B and C). The orientation corresponding to the worst hit rate count in the VM and AB day 1-tasks was assigned as the shape to be trained in the learning phase (Fig. 1D). In subsequent days subjects performed several sessions of a visual search task (Fig. 1A) which steadily improved subject's performance to detect the trained shape (Fig. 3), in agreement with a previous study (Sigman & Gilbert, 2000). Fig. 3A shows that the hit rate (proportion of trials in which the trained target was present and the subject response was correct) increased more than three times after seven visual search sessions (Fig. 3A). The increase in performance was mainly driven by an increase in the number of hits, as training did not affect the rate of false positive responses (Fig. 3B).

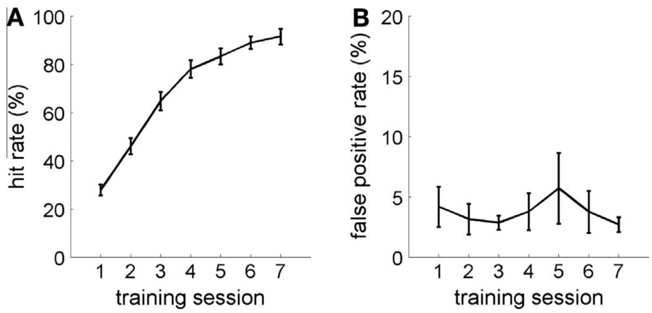

Fig. 3. Training on the visual search task improved performance. Subjects' progress through the course of learning. Each session was performed on a different day. A: Steady increase of hits (correct responses on 'target present' trials). B: False positive responses (i.e. the response was "trained target" when the stimulus was any of the untrained shapes) remain relatively unchanged with practice. Mean values are averages across subjects and error bars represents SEM.

3.2. Increased ability in visual search is transferred different in AB and VM tasks

If learning changes the efficiency of the encoded representation of the trained shape, learning should transfer to a new task as long as the stimulus location and features are maintained. Alternatively, learning could also improve the detection of a trained shape only within the context of a specific task. To distinguish between both alternatives, we compared performance on the AB and VM tasks *before* and *after* the learning phase. We emphasize that the trained shape is the same as the target in the AB and VM tasks; however, both tasks differ completely from the visual search task used during training. Moreover, the AB task has very different characteristics to the VM task, allowing us to explore the specificity of the learning transfer between tasks.

After fulfillment of the learning phase, subjects completed one session of the VM and one session of the AB tasks (Fig. 1A). Fig. 4 illustrates the effect of learning in the AB task: the hit rate of the trained target and the discriminability index d′ increased for all SOA after visual search training. A 9 × 2 within subjects ANOVA with SOA and training (before/after) as factors revealed that the effect of training was statistically significant at 0.05 significance level (see Table 2 for complete stats). The interaction effect between training and SOA was non-significant. In this analysis we only considered trials in which T1 was correctly reported (94.8% of the trials). The shape of the hit rate vs. SOA curve replicates well-known results for this task (Raymond et al., 1992). Interestingly, training did not disrupt this pattern. As shown clearly in Fig. 4A and C, the typical U-shape curve associated with the AB is shifted upwards after practice. The rate of false positive responses remain statistically unchanged, as in the visual search task.

One potential concern is that learning on the AB task was not mediated by training. Rather, it may be the case that performance on the AB task increased during the first session (pre-training phase), independent of any improvement during the visual search task. To rule out this possibility we compared the discrimination performance of the untrained targets before and after training. If learning occurred in the first session, we should see improvement on the AB task performance even for untrained shapes. As shown in Fig. 5, we found that there is a significant increase in hit rates for untrained targets with learning. However, this increase was counterbalanced by an increase in false alarms, such the d′ remained statistically unchanged during the experiment for untrained shapes (complete stats are displayed in Table 3).

In the VM task, visual search training has a fainter effect. As shown in Fig. 6, learning increased hits and reducing false positives, especially at ISI corresponding to the lowest performance (ISI ~20 ms). Also, we reproduced the classic U-shaped masking effect (Breitmeyer, 1984) but interestingly; this effect was reduced after training. Although it appears to be an effect at ISI of ~20 ms, considering the variance of SOA, the effect of training is not statistically significant (Table 4).

3.3. Learning effect on confidence is task-specific

We complemented objective detection responses with confidence reports ("¿how likely do you think your response is correct?"). Fig. 7 illustrates that the effect of perceptual learning on confidence is very different according to the task. In the AB task, learning leads to an increase in confidence for correct trials. However, in the VM task, confidence remains unchanged with training (see Tables 2 and 4 for complete stats).

We cannot fully determine what specific aspects of the task explain this difference since the task space is too big to parameterize it. However, we can enumerate the differences and call for future research to find exactly what is it that makes changes with training affect confidence or not. Instead, we address these issues from a computational modeling perspective within the framework of Signal Detection Theory (see below).

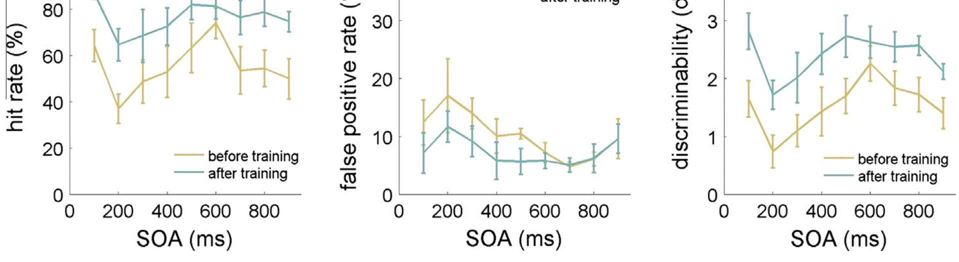

Fig. 4. Detection performance in the Attentional Blink task increased with training. A: Correct detection of the trained triangle (hit rate) before and after training sessions as a function of the stimulus onset asynchrony (SOA). Performance increases for all SOA. B: False positive responses decreased after training for SOA lower than 700 ms. C: Discriminability, combining hit and false alarm rate, significantly increased with training. See Table 2 for complete stats.

Table 2
9 × 2 within subjects ANOVA for the Attentional Blink Task.

		Hit rate		False Positive rate		Discriminability (d′)		Confidence of correct trials	
Source	d.f.	F	Prob > F	F	Prob > F	F	Prob > F	F	Prob > F
SOA	8	2.94	0.011	1.83	0.10	3.79	0.002	1.35	0.25
Training (before, after)	1	32.7	0.0023	2.59	0.17	29.26	0.003	5.74	0.06
SOA × training	8	0.67	0.71	0.56	0.80	0.65	0.73	1.17	0.34
Error	40								

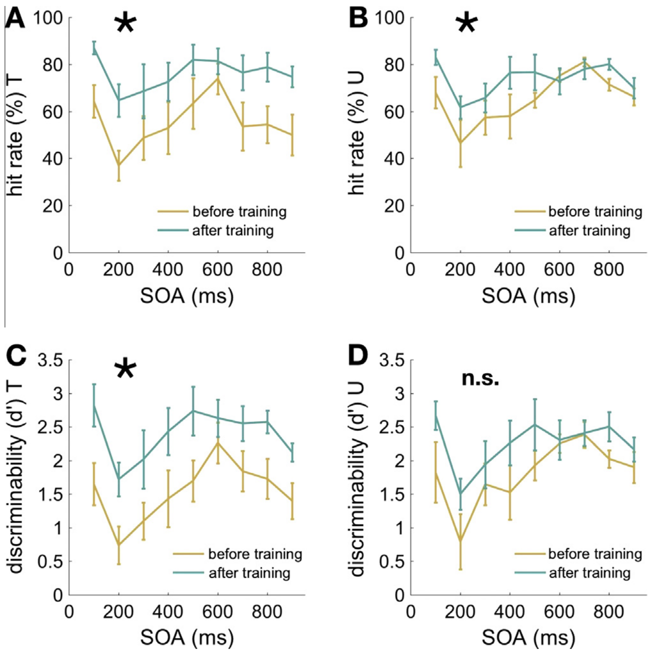

Fig. 5. Learning effect is exclusive for trained targets in the Attentional Blink task. A and B: Hit rates increased with training for both trained and untrained targets. C and D: Discrimination performance (d′) increased with training only for trained targets. See Table 3 for complete stats.

Table 3
9 × 2 within subjects ANOVA for the Attentional Blink Task for untrained stimuli.

		Hit rate		Discriminability (d′)	
Source	d.f.	F	Prob > F	F	Prob > F
SOA	8	3.85	0.002	3.27	0.006
Training (before, after)	1	7.91	0.037	5.67	0.063
SOA × training	8	2.34	0.037	1.4	0.23
Error	40				

3.4. Learning increases the signal, do not reduce noise and changes decision and confidence thresholds

We fit the behavioral data to seven different models that differ in the effect of learning on the internal representation of stimuli. The models, within the framework of Signal Detection Theory, assume that external stimuli are mapped into an internal response along a decision axis. Over trials, stimuli of class S_1 (trials in which any untrained target is present) elicit Gaussian responses with a mean corresponding to signal strength and variability corresponding to internal noise. Stimuli of class S_2 (trials in which the trained target is present) follow a similar distribution. The models assume that subjects use a decision criteria and confidence thresholds to partition the decision axis, as illustrated in Fig. 2. If the internal response is lower than the decision threshold, the subject choice is "untrained target"; otherwise, the response is "trained target". Confidence is related to the probability of being correct, increasing as the internal response moves away from the decision

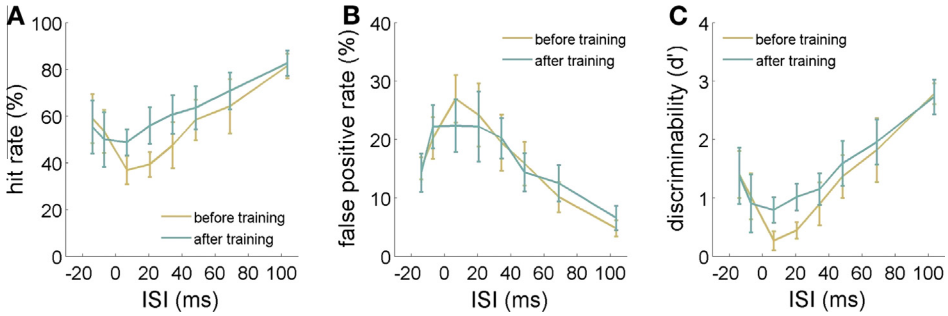

Fig. 6. Effect of training on the performance of the visual masking task. The effect of learning is fainter than in the Attention Blink Task. A: Hit rate before and after training sessions as a function of the inter-stimulus-interval (ISI). Hit rate increases for ISI ~20 ms. B: False positive responses as a function of ISI. C: Discriminability increases only for short positive ISI. See Table 4 for complete stats.

Table 4
9 × 2 within subjects ANOVA for the Visual Masking Task.

		Hit rate		False positive rate		Discriminability (d′)		Confidence of correct trials	
Source	d.f.	F	Prob > F	F	Prob > F	F	Prob > F	F	Prob > F
ISI	7	6.99	<0.001	7.73	<0.001	11.43	<0.001	8.89	<0.001
Training (before, after)	1	1.3	0.30	0.01	0.90	0.98	0.36	0.05	0.84
ISI × training	7	1.22	0.31	0.53	0.80	0.86	0.55	0.63	0.73
Error	40								

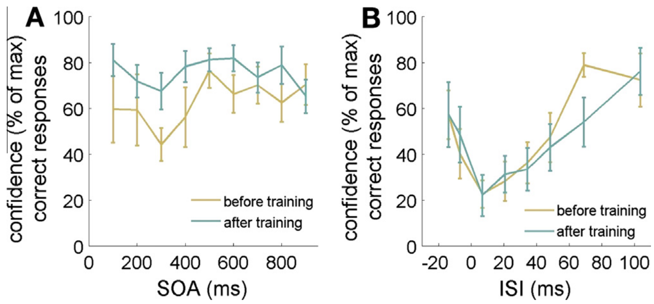

Fig. 7. Effects of visual search training on confidence ratings A. Attentional Blink task: Training increased confidence of correct responses for trials in which T2 is the trained triangle orientation B. Visual Masking task: Confidence on correct responses remained statistically unchanged with training. See Tables 2 and 4 for complete stats.

threshold. The models consider four confidence thresholds (two on each side of the decision threshold), giving rise to three confidence levels (low, medium and high). The models differ in the effect of learning on the decision parameters (Table 1). For example, model 1 assumes that learning may change the signal strength, effectively increasing/decreasing μ (the distance between the mean of the trained and untrained target distributions). It also assumes that this effect is independent of ISI/SOA. Other models (2, 3 and 7) consider that learning may reduce the internal noise in the processing of the trained target, σ_T. For a full description, please refer to Section 2.

The models were fit to the behavioral data of each subject separately. We performed a model comparison using the Akaike Information Criterion (we found similar results using the Bayesian Information Criterion) as a way to balance the likelihood of the model with the number of estimated parameters. Among all models, the behavioral data from the AB task was best accounted by model 5 (Fig. 8A). Strikingly, despite the broad differences in both tasks, the same model was also the best to account for the data from the VM task (Fig. 8B). Model 5, illustrated in Fig. 7C, considers that learning enhances the signal strength, effectively separating the internal distributions of trained and untrained stimuli, independently of SOA/ISI. It also assumes that criteria for perceptual choice and subjective confidence change with learning. As it is illustrated in Fig. 9, the 'best model' correctly accounts for summary data (hits, false positives and confidence). Individual subject data and model fitting results are shown in Fig. 10 (for the AB task) and in Fig. 11 (for the VM task).

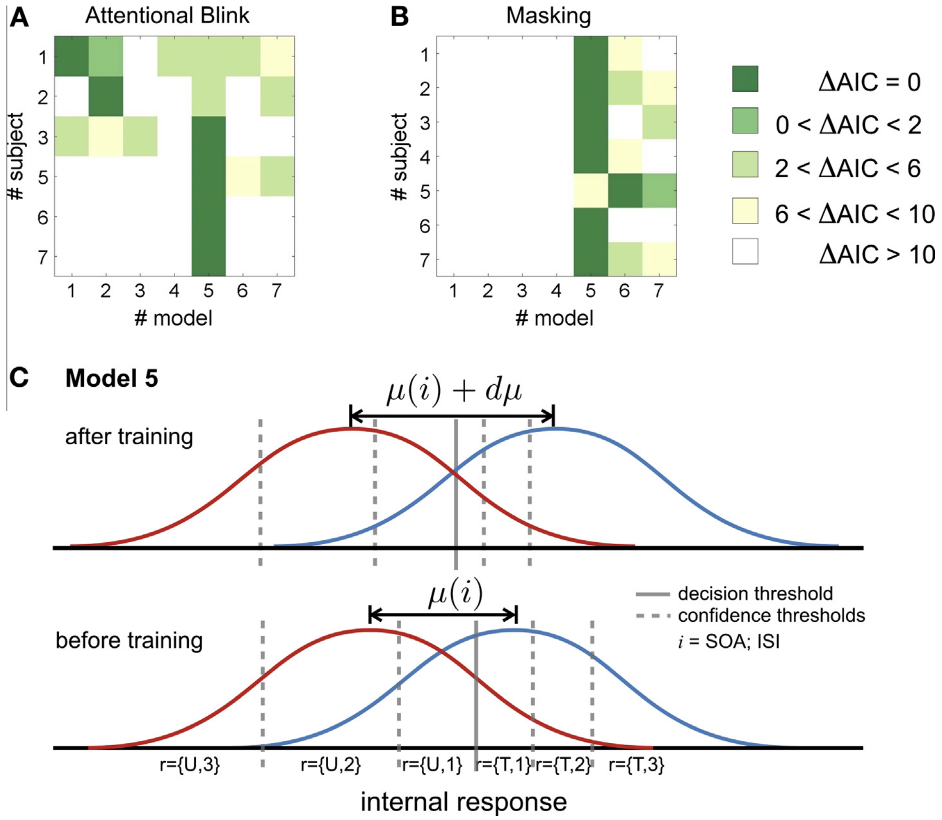

Fig. 8. Formal model comparison: We independently fitted the parameters of the models for each subject and then evaluated the quality of the fit using AIC (see Section 2). A and B: For each subject, we illustrate the difference between the AIC for model i ($i = 1, \ldots, 7$) and the AIC for the "best" model, indicated in dark green. Model 5 out-performed the rest of the models for both tasks. C: Illustration of model 5 and the effect of training on the parameters. According to this model, learning modulates the mean of the distributions of internal responses (by a constant amount, independent of SOA or ISI). The decision and confidence thresholds (vertical lines) also change with learning. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Discussion and conclusions

Perceptual learning is a lifelong process. We begin by encoding information about the basic structure of the natural world and continue to assimilate information about specific patterns with which we become familiar (Gilbert, Sigman, & Crist, 2001). This phenomenon has been largely studied in psychophysical tasks (Goldstone, 1998). In general, the learning effect is measured as changes in discrimination ability. However, this approach has largely neglected an equally important aspect of visual perception: subjective confidence.

We have shown that the effect of perceptual learning on subjective confidence is task dependent. Trained subjects improved performance and confidence when doing an attentional blink task, but on a different task setting (visual masking), confidence was unaffected by training. An intriguing question, which remains unanswered in our study, is why the two different protocols showed distinct effects on subjective learning. It may depend on the parameters chosen for each experimental task. For us, it served to show that in different contexts learning might boost subjective awareness or performance based on unconscious routing. Future studies should delimit under which precise circumstances learning results in one or the other. It is nevertheless worth noting that the temporal scales involved in each experiment are quite different: temporal intervals between target and mask are in the order of tens of milliseconds, while the temporal interval between two successive elements in the RSVP of the blink is 100 ms. Thus, it is likely that the conscious blockade of the mask cannot be overridden by learning but its implicit priming of a response be boosted. The attentional blink, on the contrary, is more dependent on fluctuations of attention and thus more likely to be overridden by learning. In addition, both tasks differ in the location of the visual field where stimuli are presented: in the AB task, stimuli appear in the center of the screen whereas in the VM task stimuli are presented in the periphery. Differences in subjective detection biases at different eccentricities (Solovey, Graney, & Lau, 2015) may also contribute to the disparity of the results between both tasks. We also acknowledge we used slightly different screen settings for training and test phases (AB and VM tasks). This might have decreased the learning transfer as it introduced subtle differences between the stimuli.

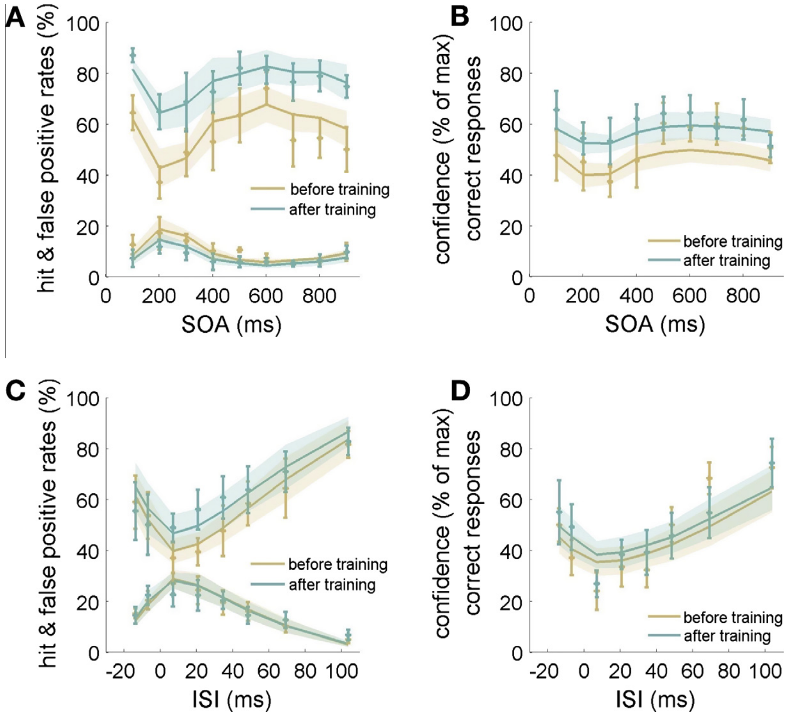

Fig. 9. Model fits to the data: Using model 5 (best model according to AIC, see Fig. 7), we calculated the model estimation of hits and false alarm rates and the confidence of correct responses. Model fits are plotted with solid lines and shades. Empirical data are shown with dots and error bars.

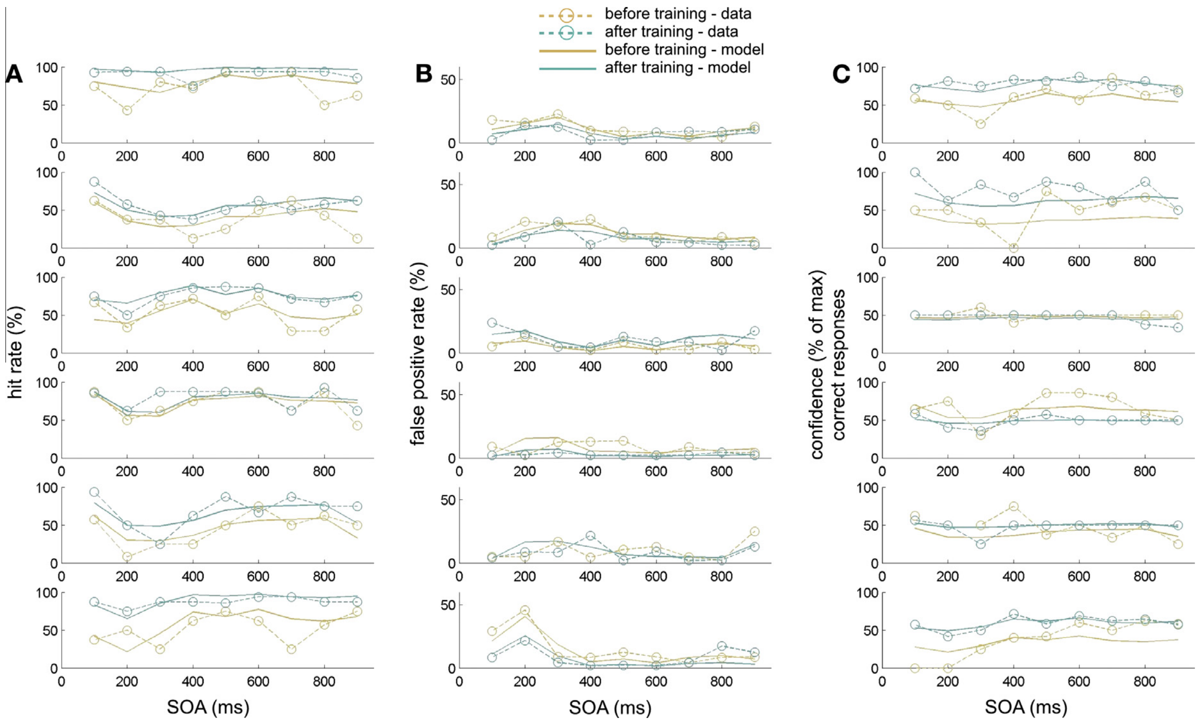

Fig. 10. Individual behavioral data and model fitting results for the AB task. Each row corresponds to a subject (from top to bottom, subject 1, 2, 3, 5, 6 and 7). Hit rate (A), false alarms (B) and confidence (C) for each subject.

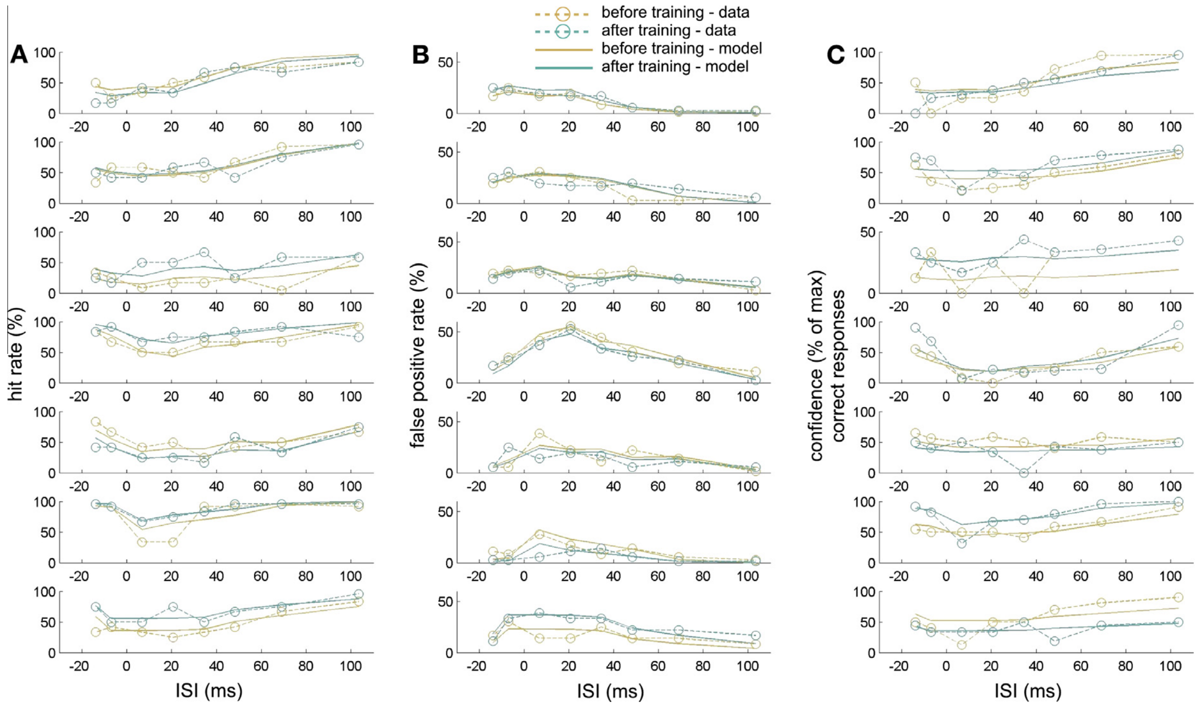

Fig. 11. Individual behavioral data and model fitting results for the VM task. Each row corresponds to a subject (from top to bottom, subject 1, 2, 3, 4, 5, 6 and 7). Hit rate (A), false alarms (B) and confidence (C) for each subject.

It may not be surprising to find that learning depends on the task setting, given previous works at a neurophysiological level. Some experiments have shown that learning related changes of activity in sensory cortices are modulated by task-settings, both at the single neuron level (Ito & Gilbert, 1999; Li, Piëch, & Gilbert, 2004, 2006) and at macroscopic measures with fMRI (Sigman et al., 2005). In some instances, learning is state dependent in that it requires reproducing not only the same task but also the same physiological environment for both encoding and retrieval (Shulz, Sosnik, Ego, Haidarliu, & Ahissar, 2000). Nevertheless, our study provides evidence for a unifying principle.

Despite these broad differences between the tasks, formal models comparison shows homogeneities in what aspects of SDT models change with training. Specifically our analyses reveals two important principles: (1) learning changes the signal strength independently of SOA/ISI and (2) decision and confidence criteria change with learning. Models in which the confidence criteria are assumed to be the same before and after learning cannot account for the variability of the data. In agreement with previous results, we did not observe evidence for noise reduction with learning (Gold, Bennett, & Sekuler, 1999) as the improvement in discrimination ability is associated with an enhancement of signal strength. In summary, these results imply that: (a) the gain in object recognition is independent of processing time, an indication that changes in cortical representations are effective from the first spikes; (b) learning changes the internal representation of a shape, but also the decision criteria to convey choice and confidence from these distributions. These observations pose specific constrains on existing models of decision-making and on how these models can generalize to different learning and contexts.

A potential confound for the interpretation of our experimental and modeling results is that of criterion content (Kahneman, 1968). It has been argued that subjects may rely on different visual information to convey choice in visual masking tasks (Albrecht & Mattler, 2012a, 2012b; Maksimov, Murd, & Bachmann, 2011). In certain tasks, criterion content for objective discrimination tasks might differ for low and large ISI (Jannati & Di Lollo, 2012; Sackur, 2013). Our SDT-based models do not take into account differences in criterion content. However, in our experimental design we intentionally used a different task in the training phase. Therefore, it is unlikely that learning could change criterion content in AB and VM tasks.

An open question of present investigation is to determine the resolution of top-down signals. On practical terms, this has a great relevance in understanding which forms of practice may be retrieved in different contexts. A great body of knowledge has been recently built showing that broad forms of practice, such as in action video-games, may lead to very specific and controlled forms of learning (Dye, Green, & Bavelier, 2009; Li, Polat, Makous, & Bavelier, 2009). Specifically, action video-game playing can push the limits of attention, including an overall increase of performance of the Attentional Blink task (Green & Bavelier, 2003, 2006). In our study we showed, complementary to these observations that low-level learning, which is highly specific to the trained shape, can transfer to other tasks that involve processing of this shape.

To conclude, our study suggests a method to study dissociations between objective performance and introspection of task performance in a formal and quantitative manner. One avenue of work that may benefit from our approach is the relationship between attention and visual masking. It is known that pre-cueing the location of the target increases its visibility (Boyer & Ro, 2007; Bruchmann, Hintze, & Mota, 2011). However, it remains to be explored to what extent this is a selective attention mechanisms or an ignition of conscious awareness mechanisms (Bachmann & Francis, 2014). In general, our experimental design can be used to discriminate which aspects of learning affect conscious or unconscious processing and opens a window to explore, systematically, which class of tasks and processes are transparent and which are opaque to introspections.

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