Introduction

The ability of humans to detect changes in a number of visual attributes improves with practice. This has been shown for orientation (Matthews, Liu, Geesaman, & Qian, 1999), motion (Ball & Sekuler, 1987), spatial displacement (Mckee & Westheimer, 1978), vernier acuity (Beard, Levi, & Reich, 1995; Fahle & Edelman, 1995), and texture segmentation (Karni & Sagi, 1993; for a review, see Fine & Jacobs, 2002; Goldstone, 1998). Researchers have attempted to elucidate the mechanisms by which this learning process takes place. A number of psychophysical studies have measured performance in perceptual tasks in different amounts of external noise to determine whether learning is mediated by a decrease in additive noise, multiplicative noise, and/or an increase in the observers' ability to integrate information across the signal more optimally. These studies support the idea that perceptual learning improves the observers' ability to integrate over signal relevant information more efficiently (Gold, Bennett, & Sekuler, 1999; Gold, 2003; Hurlbert, 2000; Dosher & Lu, 1998; Beard & Ahumada, 1999), perhaps through reweighting of basic sensory units (Dosher & Lu, 1998).

This process might even play a greater role in the real world where perceptual tasks often involve complex stimuli encompassing visual cues, some that are relevant to the perceptual task at hand and others that are irrelevant. Tasks such as discriminating human faces and objects or searching for a target object in a visual scene require training to distinguish relevant visual cues from those that are irrelevant. When first encountering a complex perceptual task, humans are typically uncertain about which are the relevant cues that will allow them to best perform the visual task. With practice, they learn to attend (i.e., give weight) to visual cues that contain information and ignore those cues that are not informative. In this framework, attention allows the observer to differentially weight and/or select sen-

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sensors coding task relevant information (Kinchla, Chen, & Evert, 1995; Eckstein, Shimozaki, & Abbey, 2002; Murray, Sekuler, & Bennett, 2003; Shimozaki, Eckstein, & Abbey, 2003).

This particular learning process has been a central concept in classical studies of infant perceptual development and adult perceptual learning (Gibson, 1969, 2000; Goldstone, 1998). It has been referred to as learning through reduction in uncertainty.1 The uncertainty refers to the observers’ initial lack of knowledge about the visual cues that are relevant for the visual task. Gibson has also referred to the process as learning through attention optimization (Gibson, 1969, 2000; Goldstone, 1998). The process of learning through attention has also been supported by recent findings showing the ability of V1 cells in macaques to dynamically modify the processing of visual information depending on immediate behavioral requirements (Crist, Kapadia, Westheimer, & Gilbert, 1997). In addition, functional imaging suggests that perceptual learning correlates with durable neural changes at the earliest stages of the visual system. The change in processing is suggested to be modulated by top-down attentional processes from higher level cortical areas (Sur, Schummers, & Dragoi, 2002).

But how fast can the process of perceptual learning through attention optimization occur? One problem in measuring fast learning is that in typical studies, perceptual performance is calculated across groups or blocks of at least 25-50 trials, making it hard to observe short-term changes in performance. Here we propose to use a new experimental paradigm (optimal perceptual learning, OPL) to systematically study rapid learning through attention optimization.

In addition, the nature of the neural algorithm mediating this type of perceptual learning remains a second question. One useful starting point in elucidating the human learning algorithm is to compare it to that of an optimal Bayesian learning algorithm. The proposed OPL paradigm is designed so that an optimal Bayesian observer learns as trials progress, and, therefore, allows the investigator to compare the amount of learning of the human observer to that of an optimal learner.2

The use of the optimal Bayesian framework brings the same benefits it has brought to other areas of perception (e.g., detection and discrimination, Burgess, Wagner, Jennings, & Barlow, 1981; object recognition, Liu, Knill, & Kersten, 1995; Liu, Kersten, & Knill, 1999; Tjan, Braje, Legge, & Kersten, 1995; Tjan & Legge, 1999; and attention, Eckstein, Shimozaki et al., 2002; Shimozaki et al., 2003; for a review, see Kersten & Yuille, 2003; Geisler, 2003; Kersten, Mamassian, & Yuille, 2004). First, it allows researchers to compare the amount of learning observed in humans to that of an ideal learner, and, therefore, to establish a standard to which human learning can be compared for a variety of tasks. Second, it provides a framework that takes into account task complexity or stimulus information (Liu et al., 1995, 1999). This allows the investigator to disambiguate whether human perceptual learning in task A is larger than task B due to some property of the human perceptual system or whether it simply reflects stimulus information inherent to the task.

### Optimal perceptual learning paradigm

In the present OPL task, an image is presented and the observers search for one of four possible targets (elongated Gaussians with different orientations and polarity) in one of eight locations (Figure 1). Trials are blocked into groups of four, which we will refer to as learning blocks. For each learning block, a target is randomly selected from the four possible targets (with equal probability) and presented throughout a block of trials. However, on each trial, the location of the target is randomly chosen, and the task of the observer is to localize the target. In addition, on the last (4th) trial of a learning block, the observers have to identify the target present throughout that learning block. At the end of each learning trial, feedback is provided to the observers about the location of the target for that trial but not the target’s identity. At the end of the last (4th) learning trial following the identification decision, feedback is provided about the identity of the target present throughout that learning block. Figure 1 outlines the timeline of the experimental procedure. Human performance localizing the target is quantified by calculating the proportion correct localization for each learning trial (1st through 4th for the current study).

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Why would learning be expected across learning trials?

The main concept in the OPL paradigm is that on the first trial within a learning block, the observer is uncertain about the identity of the target presented. Given this uncertainty, let us assume that the observer initially monitors one sensory unit tuned to each of the four possible targets. Note, however, that it is only one sensor, out of the four sensory units, that is coding relevant information to the target being presented while the others are irrelevant (or partially irrelevant). Considering that each sensor is also transmitting noise (due to either the visual noise on the image or internal to the neural sensor), then integrating the responses (nonlinearly or linearly) across all sensors to make a decision about target location will bring additional noise from irrelevant sensors into the decision. This additional variability in the decision variable will degrade localization performance.

However, as the trials progress from the 1st-to-4th trial, the observer can use the location feedback to collect evidence about the presence of one or another specific target in that learning block. The varying amounts of evidence for each of the possible targets at the target location specified by the feedback can be used on the subsequent trial to increase the weights of sensory units tuned to targets associated with higher evidence and reduce the weight of sensory units tuned to targets associated with lower evidence. Performance in the localization task improves because of the increase in the optimality of the weighting of the different sensors.

But what is the best way to change the weights to the sensory units as the learning trials progress to maximize the amount of learning? This leads us to the theory of the optimal Bayesian learner.

Optimal Bayesian learner

The Bayesian observer allows us to establish the optimal algorithm for the perceptual learning task, and, therefore, obtain the performance improvement associated with this ideal decision rule. The ideal observer learns by using the image data in the present trial to modify the weights given to a nonlinear transformation of the responses of each sensory unit in future trials.

On each trial, the ideal observer computes the posterior probability of the signal (i.e., target) presence at each of the possible signal locations given the data at all locations (g) and chooses the location with the highest posterior probability. The posterior probability at the ith location can be related to the likelihood of the data at all locations given signal presence at the ith location, through Bayes’ rule (Peterson, Birdsall, & Fox, 1954; Green & Swets, 1966):

\[ P(i|g) = \frac{P(i) P(g|i)}{P(g)} \]  

where \( P(i|g) \) is the posterior probability of the signal being present at the ith location given the data at all locations g, \( P(i) \) is the prior probability of the signal being present at the ith location, and \( P(g) \) is the probability of the data at all locations given target presence at the ith location and is typically known as the likelihood (l), and \( P(i) \) is the prior probability of the signal being present at the ith location.

On the first trial (t = 1) of a learning block, the optimal Bayesian observer (see Figure 2) calculates the posterior probability. However, because there is uncertainty about which of the signals is present for that block of learning

\[ \pi_{t,1} \]

\[ \pi_{t,2} \]

\[ \pi_{t,3} \]

\[ \pi_{t,4} \]

Choose maximum location

\[ \sum \]

\[ \prod_{t'=1}^{t-1} \alpha_{sp,t,j} \]

\[ \pi_{t,1} \]

\[ \pi_{t,2} \]

\[ \pi_{t,3} \]

\[ \pi_{t,4} \]

Figure 2. Ideal observer decision rule for the perceptual learning paradigm. On each trial and location, the ideal observer computes the likelihood of the data given the presence of each of the four possible signals (l; left panel). It then sums the weighted likelihoods (\( \alpha \)) and chooses the location with the highest scalar response (left panel). After the decision, feedback is given about the location of the target (red circle, right panel). The optimal observer calculates the likelihood of the data given that each of the targets was present at the location specified by the feedback (right panel). The weights (priors) are updated for the next trial based on the signal likelihoods from the locations, indicated by the feedback on all previous trials (right panel).
trials, it computes the posterior probability for each of the $J$ possible signals ($J = 4$ for the task in the present work). This is equivalent to computing a ratio of the likelihood of the data at the $i$th location given signal presence ($P(\mathbf{g}_{ij} | s_j)$) and the likelihood of the data at the $i$th location given signal absence ($P(\mathbf{g}_{i,n})$) (Green & Swets, 1966). The optimal observer then sums the individual likelihood ratios across signal types to compute a sum of weighted likelihoods for each location. The individual likelihood ratios are weighted by the prior expectation of each of the possible signals. On the first learning trial, the prior is $1/J$ given that each signal has equal probability of being sampled. On trial $t$, the location with the highest weighted sum of likelihoods ($\text{SLR}_{i,t}$) is chosen as containing the target:

$$\text{SLR}_{i,t} = \sum_{j=1}^{J} \pi_{j} \frac{P(\mathbf{g}_{i} | s_j)}{P(\mathbf{g}_{i} | n)} = \sum_{j=1}^{J} \pi_{j} \ell_{i,j}$$

(2)

where $\ell_{i,j}$ is the likelihood ratio of the data at location $i$, for the $j$th learning trial and for the $j$th signal, and $\pi_{j}$ is the weight (known as the prior) given to the likelihood of the $j$th signal on the $t$th trial. For white Gaussian noise, the likelihood ratio for each location and signal is given by (Peter-son et al., 1954):

$$\ell_{i,j} = \exp[(\mathbf{s}_{j}^{T} \mathbf{g}_{i} - 0.5E_{j})/\sigma^{2}]$$

(3)

where $\mathbf{s}_{j}$ is a column vector containing the $j$th signal and $\mathbf{g}_{i}$ is a column vector containing the data at the $i$th location for the $t$th trial, and $E_{j}$ is the energy of the $j$th signal ($E_{j} = \mathbf{s}_{j}^{T} \mathbf{s}_{j}$, where the superscript $T$ stands for transpose). Note that $\mathbf{s}_{j}^{T} \mathbf{g}_{i}$ can be thought of as the response of a linear sensor (matched to the $j$th signal) and the data ($\mathbf{g}_{i}$) at the $i$th location. Also $\sigma^{2}$ is the variance of the noise at each pixel.

Figure 2 (left panel) shows a schematic of the ideal observer’s decision rule for the current task.

After the 1st trial decision, feedback is given about the target location. The ideal observer has perfect memory. Therefore, the algorithm retains the likelihood of the data at the target present location for each of the $J$ possible signals:

$$\ell_{sp,i,j} = \exp[(\mathbf{s}_{j}^{T} \mathbf{g}_{sp} - 0.5E_{j})/\sigma^{2}]$$

(4)

where the subscript $sp$ for the likelihood and the data vector $\mathbf{g}$ refers to the location that contains the signal ($sp =$ signal present). All other symbols are defined as in Equation 3.

For the 2nd trial, the optimal observer will calculate the individual likelihood ratios for each location and target for the new image. However, on this trial it will weight (i.e., $\pi_{j}$, the prior in Equation 2) the 2nd trial likelihoods for each signal by the calculated likelihoods from the signal present location of the 1st trial ($\ell_{sp,i,j}$, Equation 4). In other words, if there was more evidence for one of the signals on the 1st trial, then the optimal observer increases the weight to that signal on the 2nd trial. This process is repeated for the 3rd and 4th trials, updating the prior for each possible signal with the likelihoods from the previous trials as given by

$$\pi_{j,t} = \prod_{t=1}^{t-1} \ell_{sp,i,j}$$

(5)

The likelihood ratio for the data at the signal present location in the $t'$ trial given a particular signal $j$ ($\ell_{sp,r',j}$) is calculated by Equation 4.

On each learning trial, Equation 2 with the updated prior is used to make the localization decision. Figure 2 (right panel) shows a schematic of the process of prior update (Equation 5) for the optimal observer. As the learning trials progress, the prior for the signal increases relative to that of the irrelevant elements. Figure 3 shows development of the weights or priors for each of the possible signals as the learning trials progress for the localization of one of 4 elongated Gaussians (only for those trials in which signal 1 was the target). For presentation purposes, the graph shows the priors normalized on each trial so that they sum to 1 ($\pi_{j,t,NORM} = \pi_{j,t}/\sum_{j=1}^{J} \pi_{j,t}$). This normalization does not affect performance of the optimal Bayesian model. Figure 3 shows that on average the progression of the prior for signal 3 toward zero is slower than for signals 2 and 4. This is explained by the fact that for our stimuli, signals 1 and 3 are partially positively correlated.

Figure 4 shows performance for the optimal observer as a function of trial number in the block of trials for different signal contrasts. The amount of learning of the ideal observer varies with the signal contrast. For both low and high signal contrasts, the optimal learner shows little learning. The reduced learning at high signal contrast is explained by the ceiling effect on localization performance. At
low signal contrasts (signal-to-noise ratios; \( \text{SNR} = \frac{\sqrt{s'}}{\sigma} \)), the reduced learning is due to the fact that the impoverished image information (low signal-to-noise ratio) does not allow the optimal model to calculate priors that reliably favor the signal present in the block of trials. As a result, the progression of the signal relevant prior (normalized) toward unity will be much slower and will lead to reduced learning.

Identification decision rule

To make a decision about the identification of the signal on the 4\(^{th}\) learning trial, the optimal observer calculates the joint likelihood of the data at the signal present location on the 1\(^{st}\) through 4\(^{th}\) trials given the presence of each of the possible signals and chooses the signal with the highest likelihood. The joint likelihood across all trials is calculated as

\[
\ell_{j,t} = \prod_{t'=1}^{t} \ell_{sp,j,t'}
\]  

Efficiency signatures

One way to compare human performance with respect to the optimal observer is through a measure known as the efficiency (Barlow, 1980), defined as the ratio of squared contrast threshold required for the ideal and human observers to reach a given performance level (e.g., \( P_c = 80 \% \)):

\[
\text{Efficiency} = \eta = \frac{c_{\text{ideal},t}^2}{c_{\text{human}}^2}
\]  

If the method of constant stimuli is used in the experiment, the denominator of Equation 7 is the contrast used in the experiment that led to an observed proportion correct (\( P_c \)). For the numerator, the investigator calculates the signal contrast that leads the ideal observer to perform at that same level (\( P_c \)) measured experimentally for the human observer.

In the context of the perceptual learning paradigm, the efficiency can be calculated for all \( t \) learning trials:

\[
\eta_t = \frac{c_{\text{ideal},t}^2}{c_{\text{human}}^2}
\]

Note that the denominator does not change with learning trial (i.e., the contrast used in the experiment is the same for all learning trials). However, human performance does change as a function of learning trial, so for each trial the investigator needs to calculate the contrast that leads the ideal observer to the measured human performance for that learning trial. Figure 5 illustrates graphically the process of obtaining the contrast for the ideal observer to achieve an experimentally observed performance (\( P_c \)).

Figure 5 plots proportion correct versus contrast for different learning trials for the ideal observer. For each learning trial, the corresponding curve can be used to find the signal contrast required by the ideal observer to achieve the empirically measured human performance.

The efficiency as a function of trial number can then be plotted to give rise to different learning signatures.
(Figure 6): (a) An observer that learns as much as the ideal observer has a constant efficiency as a function of trial number (complete learning); (b) an observer that does not learn as much as the ideal observer, partial or incomplete learning, has a decreasing efficiency with increasing trial number; (c) an observer that learns more than the ideal observer has an efficiency that increases with trial number (over-complete learning); and (d) an observer that learns slower than the ideal observer will have an early drop in efficiency followed by an increase in efficiency in the last learning trials.

Relative entropy

Figure 3 shows the evolution across learning trials of the priors for the optimal observer. It would be useful to be able to quantify the departure of the prior distribution from the initial uniform prior distribution. A distance metric in information theory to quantify the similarity between two sets of probabilities is the relative entropy or Kullback-Liebler divergence (Kullback, 1959). Here we use the relative entropy to assess how a model’s distribution of priors compares to the set of uniform priors in the initial trial of a learning block, where there is maximum uncertainty about which signal is present for that block of trials. For our task, the relative entropy can then be defined as (Kullback, 1959)

$$D_t = \sum_{j=1}^{N} \pi_{j,t} \log_2 \left( \frac{\pi_{j,t}}{1/N} \right),$$

where $\pi_{j,t}$ is the weight for the $j^{th}$ signal on the $t^{th}$ trial, and $1/N$ stands for the uniform priors at the initial learning trial.

Figure 7 shows the relative entropy for the ideal Bayesian observer for the present task as a function of trial number. Note that the relative entropy will measure how the distribution of priors of a model departs from uniform distribution irrespective if the prior for a probable signal being favored corresponds to the signal actually present in the block of trials. Thus, the relative entropy as a function of learning trial measures how the distribution of priors converges to unity for one signal (and zero for the remaining signals), irrespective of the optimality of the process. Figure 7 shows that how the relative entropy will also depend on the signal-to-noise ratio.

Suboptimal learning algorithms

Often, replacing the optimal decision rule with suboptimal strategies can be useful. If the suboptimal model’s performance is lower than human performance, it could be argued that the human neural algorithm cannot be the suboptimal decision rule tested. In our context, if the amount of learning of the suboptimal model is inferior to that of humans, then the model could arguably be rejected as a model of human learning.

Here we consider three suboptimal rules to update the priors: (1) prior update based on the chosen location; (2) prior update based on the chosen location for correct previous trials and no prior update for incorrect previous trials; and (3) linear prior update rule.

Prior update based on the chosen location

Prior studies have shown that human observers have limited capacity memory (unlike the ideal observers) for complex visual patterns (e.g., Luck & Vogel, 1997). In this context, one possibility is that observers do not use the location feedback because they are unable to remember the image data presented at that location to efficiently update the priors. Instead, the observers might update their priors...
Suboptimal model uses the linear response of the sensor (template) to the data rather than the likelihood to compute the priors:

$$r_{j,t} = s_j^T g_{sp,t} + b$$  \hspace{1cm} (13)

where $r_{j,t}$ is the linear response of the sensor matched to the $j^{th}$ signal, $s_j$ is a vector containing the elements of the $j^{th}$ signal, $g_{sp,t}$ is a vector containing the data at the signal present location for the $t^{th}$ learning trial, and $(b)$ is a constant added to avoid negative priors.

On each trial the priors are updated by multiplying by the responses to the signal present location:

$$
\pi_{j,t} = \prod_{t'=1}^{t-1} |r_{j,t'}|
$$

The algorithm is suboptimal and will, therefore, result in less learning than that of the optimal observer. Figure 8 shows that the relative entropy for the linear prior update model increases slower as a function of trial number than both the “update priors in correct trials only” model and the optimal observer.

**Methods**

**Psychophysical experiments**

The signals were 2D elongated Gaussians (major axis $SD = 0.301^\circ$, 8 pixels, and minor axis $SD = 0.075^\circ$, 2 pixels) with one of four orientations: $0^\circ$, $45^\circ$, $90^\circ$, and $135^\circ$ with two polarities: (1) positive for the $0^\circ$ and $90^\circ$ orientations; and (2) negative for the $45^\circ$ and $135^\circ$ orientations (see Figure 1).

Noise was spatially uncorrelated (white) Gaussian noise with a SD of 4.9 cd/m$^2$ (25 gray levels of the linearized luminance scale).

Figure 8. Relative entropy as a function of learning trial for (a) the optimal Bayesian observer (empty triangles); (b) “prior update based on correct trial only” model (empty squares); (c) “prior update based on chosen location” model (x); and (d) linear prior update model (circles).
The signals were randomly located at one of eight locations equidistant along a circle with radius 3.384°. Possible signal locations were surrounded by black boxes subtending an angle of 1.805°.

The mean display luminance was 25 cd/m² and was calibrated to result in a linear relationship between digital gray level and luminance. Experiment images were displayed on an Image Systems M17LMAX monochrome monitor with maximum resolution of 1664 x 1280 pixels (Image Systems, Minnetonka, MN).

Three naïve observers participated in the study (two females, one male, aged 20-23 years with normal or corrected acuity). Viewing distance was 50 cm.

The observer initiated each trial by pressing the left button of the computer mouse. On each trial, the test image containing the signal plus noise was briefly presented for 200 ms. A response image followed containing the black boxes but no signal nor external noise. Observers chose a target location by placing the cursor inside a box and pressing the left button of the computer mouse. Feedback about the location of the target was provided using a red circle that appeared inside the box that had contained the target. At the end of the 4th trial, the observer was asked to make an identification decision by placing the mouse cursor on top of one of the four high-contrast copies of the possible signals that were shown on the top of the screen.

Each observer participated in 12 sessions of 100 learning blocks, resulting in a total of 4,800 trials. Proportion correct signal localization was calculated for each observer and learning trial (averaged across the 1,200 learning blocks). Proportion correct identification of the signal in the 4th learning trials was also calculated.

### Model simulations

Because of the nonlinear nature of the decision rules by the optimal Bayesian observer and suboptimal models, all model performances were calculated using Monte-Carlo simulations based on 20,000 trials per data point. The same signals and external noise values were used in the psychophysical experiment and the simulations. For each trial, the decision about localization was made using the rules described in Equations 1 through 5. For the suboptimal models, the prior updates were based on Equations 10 through 14.

### Results

#### Overall learning

Figure 9 shows human localization performance (proportion correct, \( P_c \)) as a function of trial number for three naïve observers. Although absolute performance was significantly different across observers, all three observers showed similar improvements with learning trials. Average improvement in \( P_c \) from the 1st-to-4th learning trial was 6.5% for KC, 6.2% for AB, and 7.5% for LL. All improvements were statistically significant (\( p < .01 \)). For all observers, the largest improvement occurred between the 1st and 2nd learning trials (Figure 9).

#### Efficiency

Figure 10 shows efficiency as a function of learning trial number for the three observers. The efficiency decreased from the 1st-to-4th learning trial by 5.34% for KC, 4.36% for AB, and 4.34% for LL. Measured as a percentage of the efficiency in the 1st learning trial, the decreases represent a 20.3% (KC), 27.9% (AB), and 21.7% (LL) reduction. Patterns of efficiency as a function of trial number were similar across all three observers.
Comparison to suboptimal models

Figure 11a and 11b compare the overall learning in humans to that of a number of suboptimal models (the ideal observer is shown on Figure 11a for comparison). Figure 11a compares human learning to “update priors on correct trials only” model. The contrasts of the signals were adjusted for the models so that their localization performance matched that of human on the 1st trial. Learning for the “prior update on correct trials only” model was larger than human learning. Figure 11b compares human performance to two other suboptimal models: linear prior update model and “prior update based on chosen location” model. Results show that the linear prior update model resulted in learning comparable to that of human; however, learning on the 2nd trial seems to be lower than human, whereas learning on the 4th trial seems to be consistently larger than human. On the other hand, the “prior update based on chosen location” model resulted in virtually no learning.

Learning contingent on correctness of the 1st learning trial

Figure 12a shows human localization performance (proportion correct) as a function of trial number for 2nd, 3rd, and 4th learning trials for those trials in which localization on the 1st trial was correct (continuous lines) versus those in which the localization on the 1st trial was incorrect (dashed lines). For all three observers, performance improvement across learning trials was significantly larger for trials in which the observers correctly localized the signal on the 1st trial. Figure 12a-12c show localization performance for correct and incorrect localizations on the 1st trial for the optimal Bayesian observer, the “prior update on correct trials only” model, and the linear prior update model. Both the optimal Bayesian and linear prior update models also showed sequential effects, but the effects were smaller than those in humans. The sequential effects for the “prior update on correct trials only” model were more comparable to the lack of human learning on 2nd trials, following incorrect 1st trial localizations (Figure 12a vs. 12c).

Signal identification performance on the 4th learning trial

Figure 10 shows proportion correct identifying the signal on the 4th learning trial for all three observers (plotted above the x-axis label: ID): 0.959 (KC), 0.848 (AB), and 0.83 (LL). The identification efficiencies were 11.23% (KC), 4.75% (AB), and 4.28% (LL).

Discussion

The importance of comparing human learning performance to the optimal Bayesian learner

Our results (Figure 9) show that humans are able to quickly improve in their localization performance within a few trials (4 trials; < 1 min). Also, human performance increases fast between the 1st and 2nd learning trials and slower after the 2nd trial. This early fast learning followed by reduced late learning might be interpreted to reflect two learning algorithms or different learning-dependent neurophysiological events evolving within different time frames (Atienza, Cantero, & Dominguez-Marin, 2002). However, comparison to the optimal Bayesian learner suggests otherwise. The larger amount of learning from the 1st-to-2nd learning trial is also present in the optimal observer (Figure 11), suggesting that this effect is not particular of the human neural learning algorithm but might be a property inherent to the task and stimuli. Furthermore, the efficiency analysis (Figure 10) shows that for all three human observers the largest drop in efficiency occurred between the 1st trial and the 2nd learning trials. This suggests that even though humans learned the most between the 1st
Sources of suboptimal human learning

One possible source of inefficiency in the human learning is imperfect visual memory (Luck & Vogel, 1997). The ideal observer perfectly remembers the image presented at the location indicated by the feedback, and in updating the priors is limited only by the external noise on the image. In contrast, humans are probably updating their priors based on a lower quality memory representation of the image. This lower quality representation can be modeled by adding “memory noise” into the image at the feedback location. This would result in more unreliable prior updating and would, therefore, lead to inefficient learning.

One striking result of our analysis of localization performance is that human observers failed to learn at all on 2nd trials following incorrect 1st trials (Figure 10a). This result suggests that observers were unable to use the location feedback following incorrect localization decisions to update the signal priors. This outcome might be due to observers’ inability to remember the image presented at a missed target location.

On the other hand, the results also support the idea that observers used the feedback informing them that they had chosen an incorrect location to leave the priors unchanged for the next trial following incorrect localization trials. If humans had ignored the feedback altogether and updated their priors based on image data from an incorrectly chosen location that only contained noise, then they would not show any learning at all (as predicted by the “update priors based on chosen location” model, Figure 11b).

Sequential effects in perceptual judgments for human and optimal observers when learning about signals

It has been previously observed that in many basic experiments, a human observer’s response on a given trial is influenced to some extent by the stimuli and responses on immediately proceeding trials (Green & Swets, 1966; Green, 1964; Atkinson, Carterette, & Kinchla, 1962; Kinchla, 1964). This observation violates one of the fundamental assumptions of the typical signal detection theory analysis and optimal decision making. These dependencies have typically been related to fluctuations in alertness...
One interesting result arising from the present work is its relation to sequential dependencies in the beginning trials of a psychophysical study: the fact that the probability of a correct trial is larger if the previous trial was correct than when it was incorrect.

These dependencies could be explained if we note that often when first faced with a new perceptual task, the observer is uncertain about the signal he/she is looking for and by assuming that observers are updating their priors as trials progress.

Our present theoretical results for the present task show that even an optimal observer with uncertainty about target parameters and learning about the target from trial to trial via prior updating will give rise to sequential effects (see Figure 12b). This result might seem counterintuitive given the statistical independence of the decision on each trial. However, the sequential effects in the optimal Bayesian observer are explained by the fact that the prior updating of a given trial depends on the information presented on earlier trials, breaking the statistical independence of the decisions on each trial. For example, for the present OPL paradigm, first trials that led to a correct localization are typically associated with more evidence (higher likelihoods) about the relevant target than incorrect localization trials. Therefore, the prior corresponding to the relevant target will be larger for 2nd trials in which localization was correct on the 1st trial. Figures 13a and 13b show the prior updating for correct and incorrect 1st trial localization trials for an optimal Bayesian observer for learning blocks with signal 1 as the target. Note that for the 2nd learning trial, priors for signal 2 and 4 are close to zero following 1st trials with correct localization (Figure 13a), whereas they are non-zero following 1st trials with incorrect localization (Figure 13b). In addition, the weighting of the relevant signal 1 is 0.8 following 1st trials with correct localization and is 0.6 following 1st trials with incorrect localization. This higher weighting of the relevant target will lead to higher performance localizing the target on 2nd trials following correct 1st trials (Figure 12a).

However, note that our results show that for the three human observers (Figure 12b), the dependency of performance of the 2nd trial on whether the 1st learning trial was correct is much larger than that of the optimal observer and also than the linear prior update model (Figure 12d).

The human result is more comparable to that of a model that does not update priors on incorrect trials (Figure 12c). Figure 13c shows the development of the priors on incorrect trials for such a model. The priors on the 2nd trial following incorrect 1st trials are unchanged leading to no performance improvement from the 1st-to-2nd trial (Figure 13c).

**Relationship to other perceptual learning paradigms using external noise**

There is a growing literature assessing mechanisms of perceptual learning across blocks of hundreds of trials using external noise (Gold et al., 1999; Dosher & Lu, 1998; Li, Levi, & Klein, 2004; Lu & Dosher, 2004). Possible mechanisms of improvement of performance include (a) better tuning of the perceptual template; (b) reduction in internal noise; and (c) change in nonlinear properties such as transducer and/or intrinsic uncertainty.

Most of these studies have shown that template retuning is responsible for the perceptual learning, perhaps related to the observers’ increasing ability to use full knowledge about the visual properties of the signal as the trials progress. In the present study, we explicitly manipulated the uncertainty about the signal. We did not consider the possibility that the learning across trials is due to a reduction in constant additive internal noise. In the context of the OPL experimental paradigm, learning due to a reduction in internal noise would require that internal noise cyclically decreased from the 1st-to-4th learning trials and with the unlikely scenario that internal noise reset itself to a high level for the 1st learning trial of the next learning block.

![Figure 13. a,b, and c. Average progression of priors for each signal as a function of learning trial in learning blocks in which the signal 1 was present for (a) correct 1st localization trials for the Bayesian Ideal observer and the “update in correct trials only” model, (b) incorrect 1st localization trials for the optimal observer, and (c) incorrect 1st localization trials for the “update in correct trials only” model.](https://jov.arvojournals.org/pdfaccess.ashx?url=/data/journals/jov/933504/)
Instead, the present work considered models that improved their ability to integrate information across possible signals nonlinearly akin to the optimal Bayesian model. However, it might be that a suboptimally linear model that integrated information across possible signals in a linear way might be able to account for the data. Future work will attempt to discriminate between a fully linear model and the multiple templates nonlinear models investigated in the present work.

Conclusions

We have introduced a new experimental paradigm to systematically and quantitatively study the dynamics of perceptual learning by comparing human learning to that of an optimal Bayesian learner. The paradigm provides a general and flexible framework that could be used to study the process of learning in a variety of tasks and sensory modalities. Our results in the context of localization of a target with uncertainty about orientation and polarity show that humans can rapidly learn (within 4 trials), although less than an optimal observer (average percentage drop in efficiency from 1st to 4th trial = 23.3%). The largest improvement in human performance, occurring from 1st to 2nd trial, reflects a property inherent to the visual task and not a property particular to the human perceptual learning mechanism. One important difference between the human and ideal observer is that human learning relies (suboptimally) more heavily on previous decisions than on the feedback, resulting in no human learning on trials following an incorrect localization decision.

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Footnotes

1 Note that uncertainty in this context is used to refer to the general idea of lack of full knowledge about the visual properties of the signal being presented and not to a particular nonlinear decision rule to integrate information across possible signals, such as in previous work (Pelli, 1985; Eckstein, Ahumada, & Watson, 1997).

2 Previous studies have compared human performance with respect to an ideal observer in a standard task in which an ideal observer does not learn (Gold et al., 1999). Thus, these studies allow for the identification of the mechanism mediating the learning; they do not allow for comparisons of the amount of learning in humans and in an optimal learner.

References


