Research Article

The Functional Form of Performance Improvements in Perceptual Learning

Learning Rates and Transfer

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ABSTRACT—*The functional form of performance improvements has been extensively studied in speeded cognitive and motor tasks; in such tasks, reductions in response times have been characterized by the ubiquitous power law of learning or by a simpler exponential form. Performance improvements in perceptual capacities are also important in expertise, but their functional form is unknown. This study investigated the functional form of perceptual learning. For individual observers, reductions in thresholds were best described by an exponential function, rather than a power or compound exponential and power (apex) function. Learning was specific to orientation, a result that supports the perceptual locus of the learning, and was decoupled in high and low external noise, a result that reflects separable learning mechanisms in the two conditions. The simple exponential form of learning implies a constant relative rate of learning throughout practice; there was no evidence supporting multilevel hypotheses, such as serial reverse hierarchical and parallel-learning models, that posit multiple processes of learning characterized by different rates.*

Human action occurs within a complex perceptual world. The role of practice in motor tasks and in cognitive tasks is widely recognized. However, practice also plays a significant role in the rapid analysis and categorization of visual, auditory, and tactile objects in expert perceptual behavior. Practice improves performance in the majority of perceptual tasks and has been studied in all sensory modalities (Fahle & Poggio, 2002). The fact that these improvements often are specific to some aspect of the stimulus and task, such as location, orientation, or spatial frequency, supports the idea that this learning has a perceptual locus. Perceptual learning may reflect plastic changes at early levels of the visual system (Karni & Sagi, 1991), learned reweighting of stable early representations (Dosher & Lu, 1998), or a reverse hierarchical cascade from rapid learning at late visual areas to slower learning at earlier visual areas (Ahissar & Hochstein, 1997). In the study reported here, we asked fundamental questions about the functional form of perceptual learning, about which little is known, for a basic visual task (Gabor orientation identification) with stimuli approximately matched to early visual analysis. Our goal was to understand the nature and architecture of the improvements during perceptual learning.

In domains other than perceptual learning, from motor learning to repeated retrieval of facts from memory, the functional form of improvement has been well studied: Power laws of learning are ubiquitous—especially for response time tasks. The power function is considered a "law" of practice in speeded cognitive tasks: "Skill acquisition . . . [is] distinguished [by the] . . . power law for practice" (J.R. Anderson, 1982, p. 397; also see Logan, 1992). However, R.B. Anderson and Tweney (1997) suggested that aggregation over decreasing functions with varying rates often approximates a power function. A comprehensive reanalysis of cognitive- and motor-task response times (Heathcote, Brown, & Mewhort, 2000) found exponential improvements for single observers and tasks; the power law emerged as an artifact of averaging over subjects. The functional form of learning has been the basis for formal models of pro-

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TABLE 1
Review of Measures and Functions Reported in the Literature

Source	Task	Performance measure (dependent variable)	Unit of practice (independent variable)	Best-fitting function	Data aggregation
Ahissar & Hochstein (1997)	Texture search	Threshold SOA	Blocks	Connect	Average
Fahle & Daum (2002)	Vernier	Threshold arcsec	Blocks	Connect	Average
Li & Levi (2004)	Vernier	Threshold	ln sessions	Bilinear regression	Average
Herzog & Fahle (1997)	Vernier	Percentage correct	Blocks	Connect (regression)	Average
Saarinen & Levi (1995)	Vernier	Threshold arcmin	Blocks	Connect (linear regression)	Individual
Fahle & Morgan (1996)	Bisection, Vernier	Percentage correct	Time	Connect (linear regression)	Individual
Liu & Weinshall (2000)	Motion	d'	Sessions	Connect (regression)	Average
Matthews, Liu, Geesaman, & Qian (1999)	Motion	Log d'	Log blocks	Regression	Average
Fine & Jacobs (2000)	Complex grating	Percentage correct	Blocks	Connect	Average individual
Fine & Jacobs (2002)	Various	d'/d'_1	Blocks	Connect	Average
Crist, Li, & Gilbert (2001)	Orientation	Threshold angle	Blocks	Connect	Individual
Schoups, Vogels, Qian, & Orban (2001)	Orientation	Threshold angle	Sessions	Connect	Individual
Dosher & Lu (2005)	Orientation	Contrast threshold	ln blocks	Power	Individual
Ghose, Yang, & Maunsell (2002)	Orientation	Threshold angle	Correct trials	Exponential	Individual (monkey)
Yang & Maunsell (2004)	Orientation	Threshold angle	Trials	Exponential	Individual (monkey)
Yu, Klein, & Levi (2004)	Contrast increment	Log Δc	Sessions	Regression (exponential)	Individual

Note. SOA = stimulus-onset asynchrony; Δc = the size of a contrast increment.

cessing improvements (e.g., J.R. Anderson & Fincham, 1994; Logan, 1992) and can provide strong constraints on the models of the processes underlying learning.

Both the domain and the measure of performance in perceptual tasks are substantively distinct from the domain and measure (reaction time) of performance in cognitive or motor tasks. The same functional form of improvement may or may not apply. Table 1 lists the indices and improvement functions obtained in a sample of perceptual-learning studies. The measures used varied, and in some cases no specific function or form was reported. Other studies showed linear improvements in percentage correct as a function of practice, linear improvements in log d' as a function of log practice, exponential improvements in threshold as a function of practice, and linear improvements in log threshold as a function of log practice (i.e., a power function). In most cases, the functional form has not been systematically tested. No clear conclusions about the functional form of perceptual learning emerge from this literature. The goal of the current study was to provide a systematic evaluation.

Specifying the functional form of perceptual learning can provide information about the complexity of perceptual learning. The exponential form has a constant relative learning rate (the amount learned in each trial is proportional to the amount remaining to be learned) and is consistent with a single process. For the power function, the relative learning rate diminishes throughout practice (Heathcote et al., 2000). If learning reflects changes in several levels or processes with distinct rates, or if it reflects a cascade of improvements as in the reverse-hierarchy model (Ahissar & Hochstein, 1997), then the rate of learning may slow over time, as with a power function or more complex composite learning functions (see Fig. 1). Thus, the analysis of functional form has a new role in determining the architecture of the learning process.

We chose to measure contrast threshold—the signal contrast necessary to achieve a given accuracy level (i.e., 75%). Easily measured by adaptive-staircase methods, improvements in threshold are transparently related to improvements in discriminability in observer models (see the appendix). We adapted the methods of Heathcote et al. (2000) to evaluate the functional form of improvements by comparing exponential and power functions nested within a joint apex function (see Method). We also tested two forms of composite learning models. In one, learning is the combination of two exponential processes with different parameters. In the other, learning is a segmented or cascade process, with the second (exponential) process beginning only after significant learning in the first (also exponential).

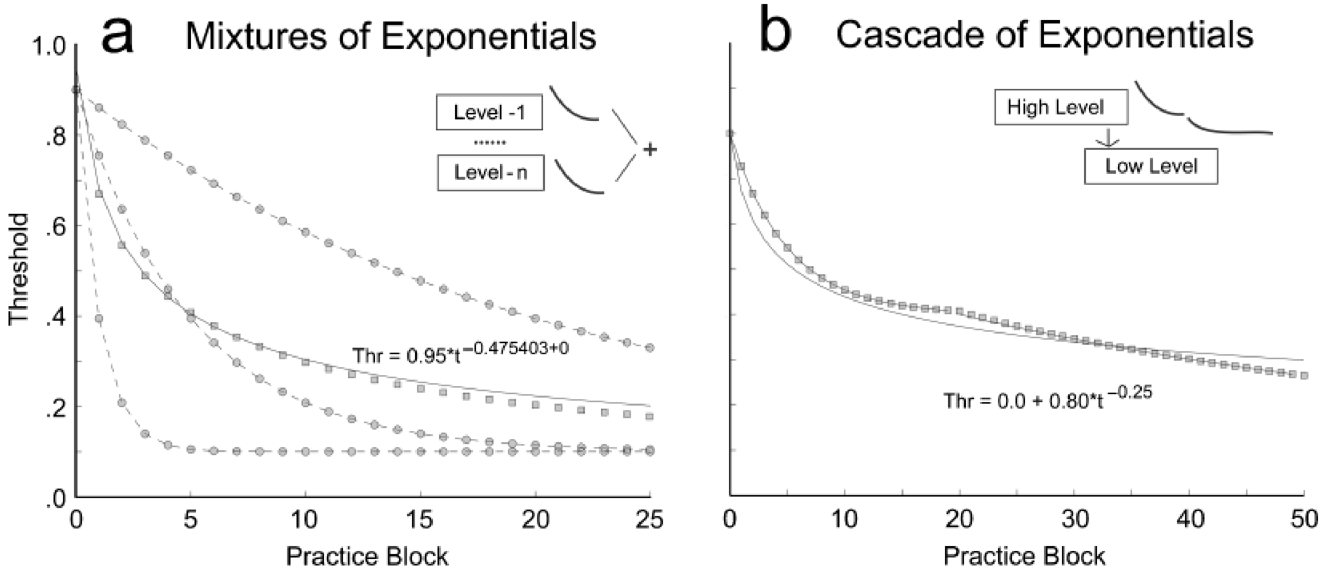

Fig. 1. Relationships between power-function forms of perceptual learning and exponential components. Power-function learning (a) emerges from aggregation over underlying curves over individuals or processes. In the example shown here, the average of three exponential functions with different rates is well fit by a power function. A cascade of two levels of exponential learning, with late learning slower than early learning (b), is also approximated by a power function. Thr = threshold.

The functional form of perceptual improvements was measured during initial training and also during a transfer test, so that we could evaluate the functional form in initial training, the extent of immediate transfer, and the form of improvements with additional training after transfer. One influential study (Liu & Weinshall, 2000) showed no immediate transfer, but doubling of the learning rate, in transfer of direction discrimination from one direction of motion to another. Another study (Fahle & Morgan, 1996) showed essentially independent learning for bisection and Vernier tasks with nearly identical stimuli. Here we studied transfer of learning between orientation judgments with different base angles.

Earlier studies showed that perceptual learning in high and low noise may reflect independent mechanisms. Improvements in high noise reflect external-noise exclusion; improvements in low noise reflect enhancement of the stimulus. These kinds of improvements may occur individually (Dosher & Lu, 2006; Lu & Dosher, 2004), mixed together (Dosher & Lu, 1999), or independently (Dosher & Lu, 2005; Lu, Chu, & Dosher, 2006). Previous results (Lu & Dosher, 2004) for foveal orientation discrimination showed "pure" perceptual learning in high external noise, but not in low noise. We measured the time course of perceptual learning of orientation discrimination at fovea in both displays with high external visual (masking) noise and displays with no noise.

EXPERIMENT

Observers were trained on Gabor orientation discrimination ($45^\circ \pm 10^\circ$ or $-45^\circ \pm 10^\circ$) at fovea. Short blocks of high- and low-noise training trials were alternated. Immediate transfer and the form and rate of subsequent training were subsequently measured for the symmetric discrimination task ($-45^\circ \pm 10^\circ$ or $45^\circ \pm 10^\circ$, respectively) to evaluate transfer.

Method

Observers

Eight paid observers with normal or corrected-to-normal vision participated. Several other subjects discontinued their participation because of scheduling issues, and 1 was eliminated because of poor task performance. Six of the 8 observers participated in the second phase of training (at least 20 measured thresholds or four sessions).

Design and Procedure

Observers discriminated briefly presented Gabor patches oriented $\pm 10^\circ$ from $+45^\circ$ or -45° at fovea. They judged whether each Gabor was oriented clockwise or counterclockwise relative to the base angle, and pressed the right ("j") or left ("f") key on a keyboard, respectively. One base angle was presented in the first phase of training and the other in the second phase (after transfer), with the order determined randomly. Two adaptive staircases measured contrast threshold (Levitt, 1971): Contrast of the Gabor patches was reduced by 10% ($c_{n+1} = 0.9c_n$) after two (2/1 staircase, 70.7% correct) or three (3/1 staircase, 79.3% correct) successive correct responses and was increased by 10% ($c_{n+1} = 1.1c_n$) after each error. The two staircases were intermixed in each block of 140 trials (60 trials of the 2/1 staircase

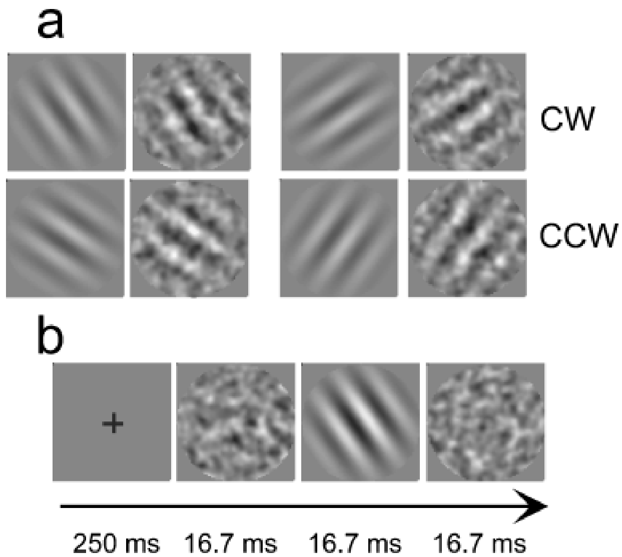

Fig. 2. Examples of the stimuli (a) and schematic showing the display sequence (b). The Gabor patches were tilted $-45^\circ \pm 10^\circ$ (left set) or $+45^\circ \pm 10^\circ$ (right set) and are shown as they appeared in noiseless displays (left column in each set) and in high-noise displays (right column in each set). On each trial, the observer identified the tilt as clockwise (CW) or counterclockwise (CCW) relative to the diagonal axis; examples of CW and CCW tilts are shown in the upper and lower rows of (a), respectively. The stimulus appearance in (a) resulted from the visual system's temporal integration of rapidly alternated Gabor stimulus and noise displays in the display sequence, shown in (b).

and 80 trials of the 3/1 staircase). In the five blocks tested during each session (day), high-noise (masked) and noiseless blocks alternated, and the initial block type alternated across sessions. Observers were trained for about 14 sessions for each phase, before and after the task transfer, with minor variation in the number of sessions.[1]

Apparatus

Stimuli were displayed by a G3 Macintosh computer using a 10-bit Thundercard videocard and Matlab 5.1 with PsychToolbox extensions (Brainard, 1997). A pseudo-gray scale was generated on a color monitor by setting R, G, and B values to be equal. A linear lookup table, gamma-corrected with a psychophysical algorithm, evenly divided the luminance range (1–39.1 cd/m^2, with midgray at 20.5 cd/m^2) into 256 levels. Linear interpolation was used to generate finer gray levels. Displays were viewed binocularly with natural pupils at a distance of approximately 65 cm in a dark room.

[1]Although most observers trained for 14 sessions in each phase, there was minor variation in the number of training sessions (e.g., 13, 15). One subject with slow learning trained for 20 sessions in Phase 1. There were fewer sessions overall in Phase 2 because the lengthy, multiday protocol resulted in scheduling problems that caused several subjects to complete fewer sessions; scheduling issues also prevented 2 subjects from participating in Phase 2.

Stimuli

Figure 2 shows sample stimuli. The signal Gabor patch was 64×64 pixels:

$$l(x, y) = l_0\left(1.0 \pm c\sin(2\pi f(y\sin(\theta)\ \pm x\cos(\theta))) \times \exp\left(\frac{x^2+y^2}{2\sigma^2}\right)\right),$$

with angle θ of $\pm 45^\circ \pm 10^\circ$, frequency f of 1/16 pixels or 1.4 cpd, standard deviation of the Gaussian spatial window σ of 16 pixels or 0.74°; c is the maximum contrast of the sine wave, and l_0 is the midgray luminance. Each 64×64 noise image had individual 2×2 noise elements with Gaussian-distributed contrasts with mean value l_0 and standard deviation $(l_{\max} - l_0)/3$, band-pass filtered around the signal frequency $(G(f, \bullet) = [1/(1 + (0.0625/f)^4)]\left[1/(1+(f/0.25)^4)\right]$ (using the *fft* and *fftinv*, the fast Fourier transform and the inverse transform), and then windowed into a circular aperture with a radius of 32 pixels (1.5°). Signal and noise frames (16.7 ms each; presented in the sequence noise-signal-noise) were combined via temporal integration.

Models and Analysis

The exponential ($c_\tau(t) = \lambda(e^{-\beta t}) + \alpha$), power ($c_\tau(t) = \lambda(t)^{-\rho} + \alpha$), and apex ($c_\tau(t) = \lambda e^{-\beta t}t^{-\rho} + \alpha$) forms of improvement were compared using nested-model-testing methods (Heathcote et al., 2000). Contrast threshold $c_\tau(t)$ at practice time t depends on α, the asymptotic threshold (after learning), and λ, the initial level of the learnable part, so $\lambda + \alpha$ is the initial threshold before training; β and ρ are the exponential and power rate parameters. The quality of fit (model error) is compared in the nested structure. If an exponential form fits best, then setting ρ at 0 (assuming the exponential form) will not significantly damage the fit relative to the fit of the apex function, whereas setting β at 0 (assuming the power form) will; similarly, if a power form fits best, then setting β at 0 (assuming the power form) will not significantly damage the fit relative to the fit of the apex function, whereas setting ρ at 0 (assuming the exponential form) will. If setting either ρ at 0 or β at 0 significantly reduces the value of r^2, this favors the apex.

Functions were fit to the average $\log_{10}$ contrast thresholds with nonlinear minimization routines (Mathworks, 1998). The log approximately equates the variance of the estimated thresholds, and so approximates a maximum likelihood solution. The percentage variance accounted for by a model is as follows:

$$r^2 = 1.0 - \left(\sum_{i=1}^{n}\left(X_i - \hat{X}_i\right)^2\right)\left(\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2\right)^{-1},$$

where X_i and $\hat{X}_i$ are the observed and predicted values, $\bar{X}$ is the observed mean, and n is the number of data points. Nested models (a model and a submodel) are statistically compared with $\chi^2 = n\ \ln[RSS_{\text{reduced}}/RSS_{\text{full}}]$, with degrees of freedom of $m_{\text{full}} - m_{\text{reduced}}$ (Borowiak, 1989). *RSS* is the residual sum of squared error for a given model. The nested-model approach is a classical method of model comparison (see also Wagenmakers, Ratcliff, Gomez, & Iverson, 2004, for other methods). The statistical test over observers is Fisher's chi-square, $\chi^2 = -2\sum_{i=1}^{n} \ln p_i$; the probability values p_i are associated with statistical tests for each of n individual observers, and the degrees of freedom is $2n$.

Results

Contrast-Threshold Learning Curves

The contrast thresholds in high-external-noise displays, averaged over the two staircases (75% mean accuracy[2]), are shown on the left side of Figure 3, which presents $\log_{10}$ contrast thresholds as a function of block of training. For all observers, practice improved performance in high external noise. This perceptual learning in high noise approximated an exponential form, shown by the linear functions on log-linear axes (for small α). Statistical tests are presented later in this section.

In contrast, perceptual learning in low noise (see the right side of Fig. 3) was mixed: Some observers learned a bit, others did not, and some showed slight deterioration in performance. These findings—perceptual learning in high external noise but no or inconsistent perceptual learning in low external noise—extend our previous results (Lu & Dosher, 2004) to the present blocked-training protocol. The dissociation of learning in the two conditions also illustrates the distinct learning mechanisms in high and low external noise.

Functional Form of Learning

The functional form of perceptual learning can be meaningfully assessed only when perceptual learning is significant, so our tests were focused on the high-external-noise condition. The approximately log-linear perceptual learning functions in high external noise (see Fig. 3) are generally compatible with an exponential form of learning. However, a (log-log) power function is also plausible. The three functions (exponential, power, and apex) were fit to the log thresholds to evaluate the functional form of learning.

In *initial learning* (Phase 1) in the high-noise condition, reduction to the power-function submodel reduced r^2s (relative to the apex solution) for all 8 observers, sign test $p < .004$, and Fisher $\chi^2(16) = 46.05$, $p < .0001$, $p_{\text{rep}} > .99$; in contrast, the r^2 values for the exponential submodel were essentially equivalent to the r^2 values for the apex solution, changing significantly for only 1 of the 8 observers, sign test $p \approx .96$, and Fisher $\chi^2(16) = 1.5$, $p \approx .9$. The data for *learning after transfer* (Phase 2) in the high-noise condition were very similar, essentially providing a replication: Reduction from the apex to the power function again significantly reduced the r^2 value for all observers (6), sign test $p < .02$, and Fisher $\chi^2(12) = 24.06$, $p < .019$, $p_{\text{rep}} \approx .93$; the reduction from the apex to the exponential function did not, significantly reducing the r^2 value for only 1 of the 6 observers, sign test $p \approx .89$, and Fisher $\chi^2(12) = 0.937$, $p \approx 1$.

For initial learning and learning after transfer in low-noise displays, only 2 subjects showed significant learning, so the statistical tests were very much weaker. Where there were differences, the exponential function provided a better fit than the power function.

In summary, the exponential function provided the best description of the functional form of improvement for individual observers, whereas the power function was statistically rejected. These results are consistent with prior findings of an exponential "law of learning" in practice effects on speeded response times in simple cognitive tasks (Heathcote et al., 2000). However, these task and measurement domains are so different that these are completely independent results.

Simulations show that combining data from decreasing functions with variation in the rate parameters over observers or conditions generally yields a power function (R.B. Anderson & Tweney, 1997). As expected, the power function provided a statistically better fit ($p < .05$, $p_{\text{rep}} \approx .88$) to the aggregate for the current data (average of 8 observers, 30 high-noise thresholds, Phase 1), although individual subjects' functions were best fit by the exponential function.

We performed additional model tests to evaluate whether additional components in a multilevel or multicomponent model of learning would provide an improved fit. The two composite models were (a) a sum of two parallel exponential learning processes, corresponding to a case in which performance improvements reflect learning at two distinct levels throughout training, and (b) a cascade of two exponential learning processes, corresponding to the reverse hierarchical organization. These models were compared with a simple exponential function. Similar to stepwise regression, the nested comparisons of the composite models with the simple exponential function test explicitly whether including more than one component function improves the description of the data. This direct test of multicomponent processes does not depend on the adequacy of the power-function approximation. In neither case did adding an additional learning factor improve the r^2 values; the estimated parameters simply reduced the composite model to the simple exponential function (0 of 8 tests in Phase 1 for each model, $p \approx .99$; 0 of 6 tests in Phase 2 for each model, $p \approx .98$). Thus, an exponential form best fit the perceptual learning data in a way that was consistent with a single learning process throughout training for this simple discrimination task.

Results for External Noise and Specificity

A multiple regression analysis compared the learning rates (slopes) in the high- and low-noise conditions. When the learning slopes (and intercepts) varied for the two conditions,

[2]The results obtained when we averaged the two thresholds were essentially equivalent to those obtained when we analyzed each threshold measured separately and fit each threshold function with learning functions within the perceptual template model (PTM) of perceptual learning (Dosher & Lu, 1999).

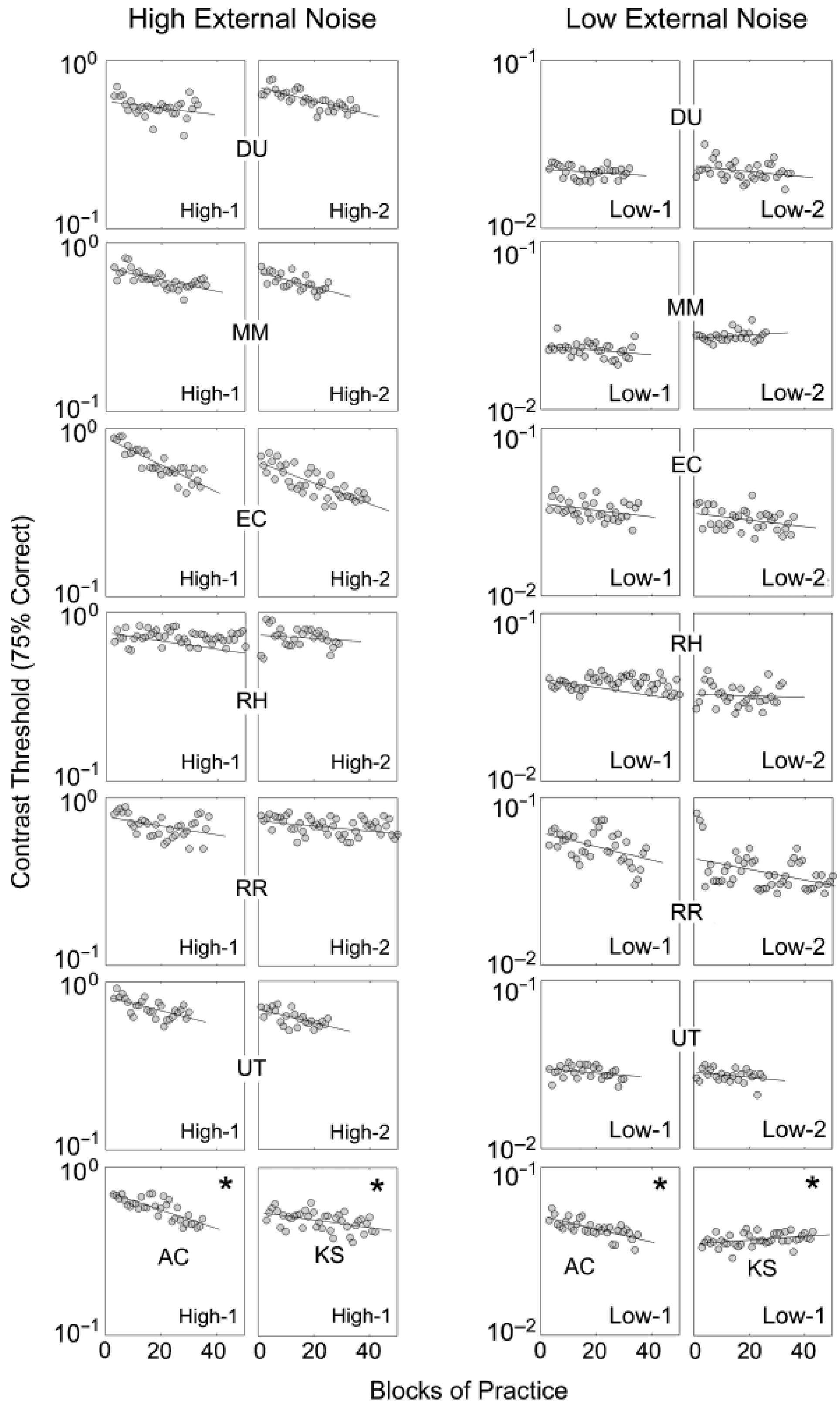

Fig. 3. Threshold performance for individual observers as a function of practice, for blocks with high (left panels) and low (right panels) external noise. Log contrast thresholds for 75% accuracy (estimated by averaging over the 3/1 and 2/1 staircases) are graphed as a function of the number of practice blocks. Each graph is labeled by the observer's initials (e.g., ''UT'') and the noise condition and phase of training (e.g., ''High-1''). Two observers (graphs marked with an asterisk) performed only the first phase of training.

the slope in the high-external-noise condition ($M = -0.08$ $\log_{10}c_\tau$/block) was about twice as large as the slope in the low-external-noise condition ($M = -.04$; mean slope ratio of 2.4, with values of 1.4, 2.0, 4.0, 1.1, 4.0,[3] 3.2, 2.5, and 0.6 for individual observers). These learning slopes were significantly different, Fisher $\chi^2(16) = 64.6, p < .001, p_{rep} > .99$, Cohen's $d = 0.53$. Thus, the learning rates were decoupled, a finding consistent with claims that learning in high noise and learning in low noise are based on independent learning mechanisms (Dosher & Lu, 1998, 1999, 2005; Lu et al., 2006); learning is more robust in high-noise environments.

We also evaluated the specificity of perceptual learning for the two different base angles trained in initial training and subsequent training (the first and second phases). After training on discriminating angles in the first phase, observers practiced a discrimination of a nearly orthogonal set of angles in the second phase. The representations of the two sets of angles in early visual cortex are believed to be independent. If there was no transfer of learning, the learning functions for the two phases should have been independent copies of the same function, reflecting independent learning. If there was transfer of learning, perceptual learning might have resulted in improved immediate performance or a faster rate of learning in the second phase (Liu & Weinshall, 2000), or both.

Transfer was tested in high external noise, the condition in which significant perceptual learning occurred. Improvements during the second phase of learning were no faster than those during the first phase, Fisher $\chi^2(12) = 0.25, p \approx .0.86$, based on a regression analysis of $\log_{10}$ threshold versus block. The average slope ratio between the two phases (slope in Phase 2/slope in Phase 1) was 1 (no difference). Only 1 subject (D.U.) showed somewhat faster learning in the second than in the first phase of training. There was some evidence for slight immediate transfer. The mean intercepts of log contrast over observers were -0.13 and -0.16 ($d = 0.73$) for the first and second phases of training, respectively (intercepts are cited in $\log_{10}c_\tau$), although 2 observers showed slightly worse performance at the beginning of the second phase than at the beginning of the first phase. Across observers, the pattern suggests nearly complete independence, as discussed in the next section.

GENERAL DISCUSSION

Perceptual learning improved contrast thresholds with practice. In this study, we explored the fundamental functional form of these improvements, about which little was known. The foveal orientation task has previously shown learning restricted to high-external-noise conditions (Lu & Dosher, 2004). The current results are similar, although a few individuals exhibited modest rather than no learning in low external noise, possibly reflecting the fact that training in the low-noise conditions was presented in separate blocks. The pattern of results reflects independent mechanisms of learning in low and high external noise (Dosher & Lu, 1999; Lu & Dosher, 2004). The functional form of perceptual learning was evaluated in high external noise, the condition in which substantial learning occurred.

Exponential functions, not the classic power function of learning nor the composite apex function, provided the best fits to the individual observers' learning data. These results parallel those of Heathcote et al. (2000) for cognitive and motor response time tasks, but for the quite different domain of perceptual learning. Many prior analyses of perceptual learning (see Table 1) considered aggregate data or a small number of data points on the performance functions. We are not aware of previous explicit analyses of the functional form of improvement for individual observers with sufficient data sets. However, perceptual learning data for individual monkeys have shown high-quality exponential fits to the performance improvements in several tasks (Ghose, Yang, & Maunsell, 2002; Yang & Maunsell, 2004). Reanalysis of our own data (Dosher & Lu, 2005) could not statistically distinguish the originally reported power-function fits and the exponential-function fits, because of small samples, but the exponential function provided a slightly better fit. Overall, then, the data are consistent with the exponential functional form for individuals. The exponential form provides a strong framework for assessing learning and possible transfer.

In a novel application of functional form analysis, the possible role of compound learning architectures in perceptual learning was tested. In no case did adding a second learning process, either in parallel throughout learning or cascaded (i.e., with the second function starting later than the first), improve the quality of fit. This result is evidence against the idea that performance improvements reflect strong contributions from learning at distinct levels with different learning rates, a notion incorporated in models featuring parallel learning (i.e., models that average local computations) or a reverse hierarchical structure (Ahissar & Hochstein, 1997). Instead, our results support a very simple architecture of learning. The current task, simple orientation judgments at fovea, is a basic task, so a single learning process may be more likely in this case than for other, more complex tasks, such as those requiring discrimination of texture or global motion. Further research is necessary.

The simple exponential form of learning found for this task does not support the influential reverse hierarchical theory of perceptual learning (Ahissar & Hochstein, 1997). The exponential form, however, may be generally compatible with a range of distributed-network models of learning for simple perceptual classifications that are well approximated as linear boundary problems (Petrov, Dosher, & Lu, 2005), and for dependent measures reflecting discriminability. A range of network models, including the Hebbian multichannel reweighting model (Petrov,

[3]This value of 4.0 was selected to represent the large ratio for observer K.S., for whom the no-noise condition was estimated to show damage rather than improvement.

Dosher, & Lu, 2005, 2006), and other stochastic error-minimization processes may approximate exponential forms (Uezu, 1997).

Training for one set of diagonal angles showed little immediate transfer to the other set of diagonal angles, and did not alter the rate of subsequent learning. This result was similar to results of Fahle and Morgan (1996) for Vernier and bisection judgments and those of Matthews, Liu, Geesaman, and Qian (1999) for line-orientation and related two-dot motion-direction discrimination. In contrast, Liu and Weinshall (2000) reported a speeded learning rate in transfer for a task requiring relatively precise discriminations of global motion orientation. The required precision of the task may have caused this difference in the results. A proposed taxonomy of task types, intended to explain variation in transfer (Petrov, Dosher, & Lu, 2005), distinguishes situations in which the original and transfer tasks (a) are distinct and use stimuli with distinct perceptual representations, (b) are the same but use stimuli with distinct perceptual representations, (c) are distinct but use stimuli that share perceptual representations, or (d) are the same but are performed under different conditions and use stimuli that share perceptual representations. Only the last case optimizes transfer. Fahle and Morgan's experiment involved a situation of the third type, with similar stimulus displays but different judgment tasks before and after transfer. The experiment of Matthews et al. was similar. The current experiment involved a situation of the second type, with separate representations but the same kind of judgment task before and after transfer. Liu and Weinshall's (2000) experiment is also of this category, but their results may differ from ours because of the high precision of the required judgment. The fact that specificity is widespread is consistent with the task analysis of perceptual learning.

CONCLUSION

Perceptual learning is an important aspect of agent expertise that has been less studied than motor or cognitive learning. We evaluated perceptual learning in a basic visual orientation task by measuring improvements in contrast thresholds. The strong specificity to the trained stimulus angles supports a perceptual locus for the improvements. We also evaluated the functional form of learning—a well-studied property of both cognitive and motor learning—in the domain of perceptual learning. Perceptual learning was best accounted for by an exponential form of improvement in perceptual discrimination with practice for individual subjects. The results were consistent with a single simple process of learning, rather than a combination of learning at multiple levels or a cascade of learning processes with different rates at different levels of visual analysis. Thus, the results are consistent with a single- rather than multiprocess architecture of learning. These results may be specific to this basic visual task, which used stimuli matched to early levels of visual analysis. Further experimental analysis should extend these results to more complex perceptual tasks.

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APPENDIX

The perceptual template model (PTM; Lu & Dosher, 1999) predicts an observer's performance, d', from fundamental signal-to-noise principles, where d' is the ratio of signal (S) and noise (N) energy:

$$\begin{aligned} d' &= S/N_{\text{total}} \\ &= (\beta c)^{2\gamma} \Big/ \sqrt{\left[N_{\text{ext}}^{2\gamma} + N_{\text{add}}^2 + N_{\text{mult}}^2\left((\beta c)^{2\gamma} + N_{\text{ext}}^{2\gamma}\right)\right]}. \end{aligned}$$

Performance improves with c, the contrast of the target (signal) stimulus, and with β, a scaling factor for the response of the template to the signal stimulus. Performance is reduced by limiting noises (N_{ext}^2, the power of the external stimulus noise; N_{add}^2, the estimated internal noise associated with absolute threshold; and N_{mult}^2, the multiplicative internal noise that increases with the contrast of the stimulus). The parameter γ controls nonlinearity in transduction ($\|\bullet\|^{\gamma}$). If we rearrange the equation, the log contrast threshold to achieve a criterion d_i is

$$\begin{aligned} \log(c_\tau) = \frac{1}{2\gamma}\log((1 + N_{\text{mult}}^2)A_f^{2\gamma}(t)N_{\text{ext}}^{2\gamma} + A_a^2(t)N_{\text{add}}^2) \\ - \frac{1}{2\gamma}\log\left(\frac{1}{d'^2} - N_{\text{mult}}^2\right) - \log\beta. \end{aligned}$$

The functions $A_f^{2\gamma}(t)$ and $A_a^2(t)$ describe learning for external noise and internal additive noise, respectively. If $N_{\text{ext}}^{2\gamma} = 0$, log threshold directly reflects $A_a^2(t)$; if $N_{\text{ext}}^{2\gamma}$ is large, N_{add}^2 is negligible, and log threshold directly reflects $A_f^{2\gamma}(t)$. Thus, the threshold measure transparently reflects improvements in discriminability.