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# A Model of Perceptual Learning Through Incremental Channel Re-weighting Predicts Switch Costs in Non-Stationary Contexts


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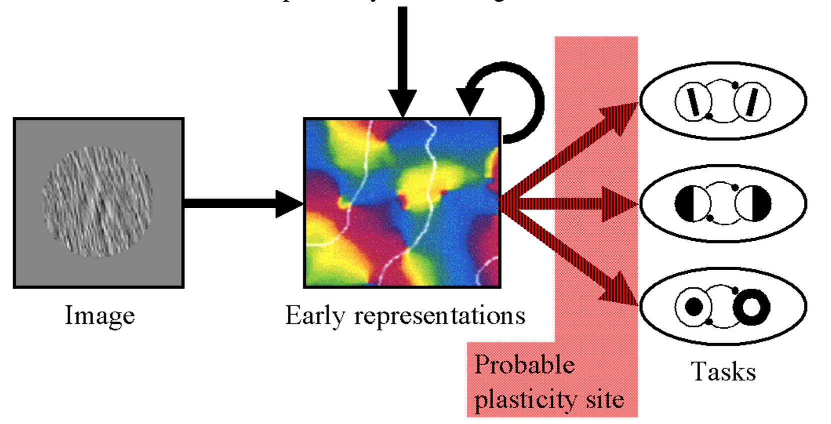
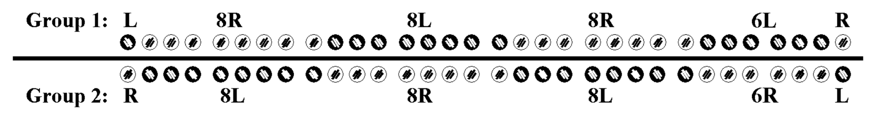
## Introduction

The orientation specificity of perceptual learning suggests a plasticity site having units tuned for orientation: V1, V2, V4. Even if learning is localized to these early areas, there still are at least two distinct possibilities as to the underlying mechanism. The representation enhancement hypothesis explains perceptual learning in terms of rectruitment of new units, sharpening of tuning curves, and/or any other changes that improve the signal-to-noise ratio of the representations. The selective reweighting hypothesis on the other hand explains it in terms of changes in the strength of the "read-out" connections to higher task-specific areas (Dosher & Lu, 1998). Both hypotheses are equally consistent with the observed stimulus specificity of learning.




There is neurophysiological evidence that the receptive field properties in V1 and V2 in adult monkeys do not change (or change but a little) as a result of non-invasive practice alone (Crist et al., 2001; Ghose et al., 2002; Schoups et al., 2001). Representation enhancement thus seems insufficient to account for the marked improvement in performance observed in all three studies.
Psychophysical demonstrations of task specificity in perceptual learning also pose challenges to the representation enhancement hypothesis (Fahle, 1997; Christ et al., 2001). The tasks used in these studies, however, tend to engage disjoint aspects of the stimulus representation and hence do not provide a conclusive test.

The present experiment is explicitly designed to use the same target stimuli, and hence presumably the same representational units, throughout. The task is also kept the same---orientation discrimination of peripheral Gabor targets. The targets are embedded in *contexts* of filtered noise whose predominant orientation alternates across epochs according to a *non-stationary schedule:*




Learning is a *process* that detects statistical regularities over time. Non-stationary environments constitute "moving targets" that challenge the learning system, thereby probing its internal mechanisms.

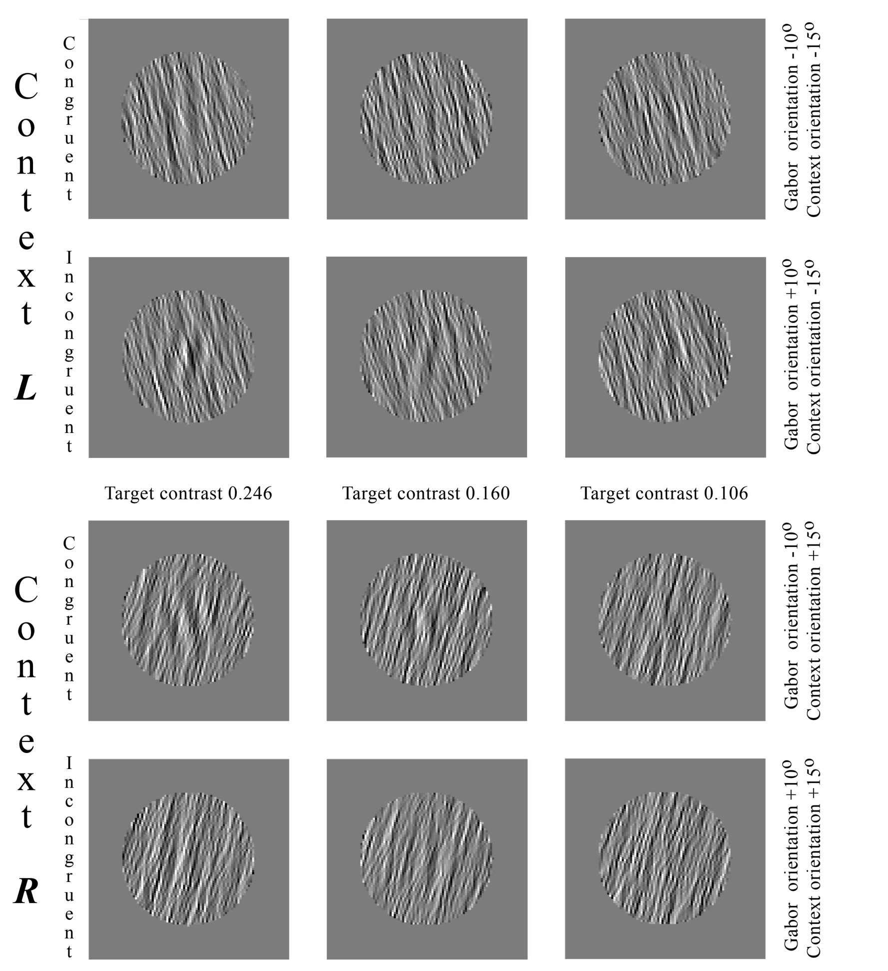
## Experiment Method

Thirteen observers were instructed to ignore the background and discriminate whether the Gabor is oriented to the left (–10°) or right (+10°) from the vertical. The stimuli were presented for 75 msec at two equiprobable locations centered either above or below fixation (+/–5 deg.vis.ang). The stimuli were rendered on a 64x64 grid subtending ~2.9 deg. vis. angle; average luminance $L_0$=15 cd/m$^2$. There were 8 sessions on separate days, 4 blocks per day. Each block consisted of 300 trials in an orthogonal factorial design: 2 Gabor orientations x 3 Gabor contrasts x 2 retinal locations. The background context was stationary within blocks and manipulated across blocks according to the counterbalanced *ABAB* schedule shown above. Auditory feedback was given on each trial.

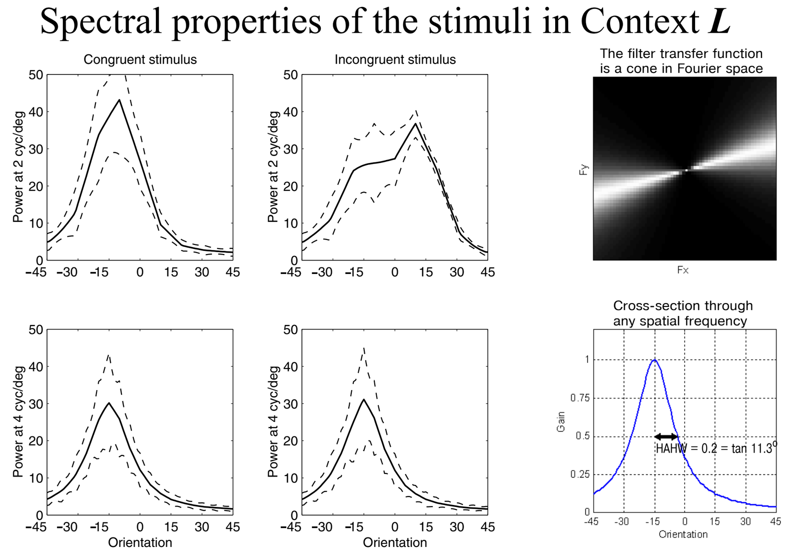
The dependent variable is the *z*-transformed probability correct and the associated $d'$. Each probability is estimated from 50 observations counterbalanced across the two retinal locations. The *z*-transformed values are then averaged across subjects. The independent variables are *Block*, *Context* (embedded within *Block*), *Contrast*, and *Congruence*.
A *congruent* stimulus is one in which the orientation of the Gabor target is consistent with the predominant orientation of the background noise.

## Stimuli

Gabor *targets* embedded in *contexts* of filtered noise




Spectral properties of the stimuli in Context *L*



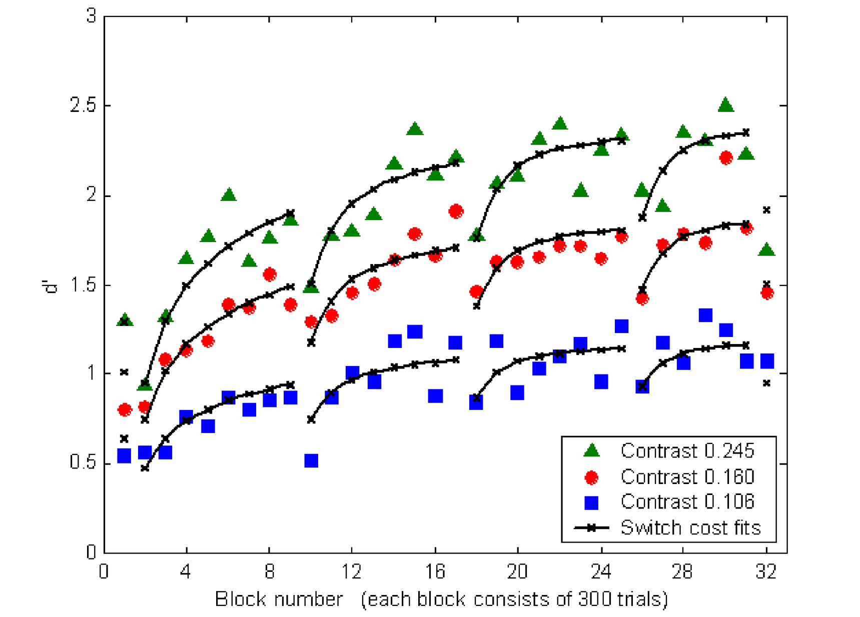

The spatial frequency of the Gabor targets is 2 cycles/degree. The background noise introduces additional variability and elevates the mean spectral power in a cone of orientations depending on context. Both left and right Gabors are present in each context and hence the region in orientation space between –45° and +45° is activated throughout the experiment.
It is difficult to conceive of any mechanism for representational recruitment or sharpening that would be affected by this context manipulation.

### Summary of the Experimental Results

* Training improves the identification performance in all conditions.
* The absolute discriminability levels depend strongly on the target contrast.
* The temporal dynamics appears largely independent of contrast.
* The accuracy drops temporarily whenever the context changes (*switch cost*).
* The switch cost seems to persist for at least 5 switches and 9600 trials.
* The identificaiton accuracy for congruent stimuli tends to decrease slightly when the target contrast increases!
* A small (57% vs. 43%) but persistent response asymmetry favors the background orientation.
* There is sequential assimilation towards the previous stimulus and response.
* The response times mirror most patterns in the accuracy data.

## Empirical Results

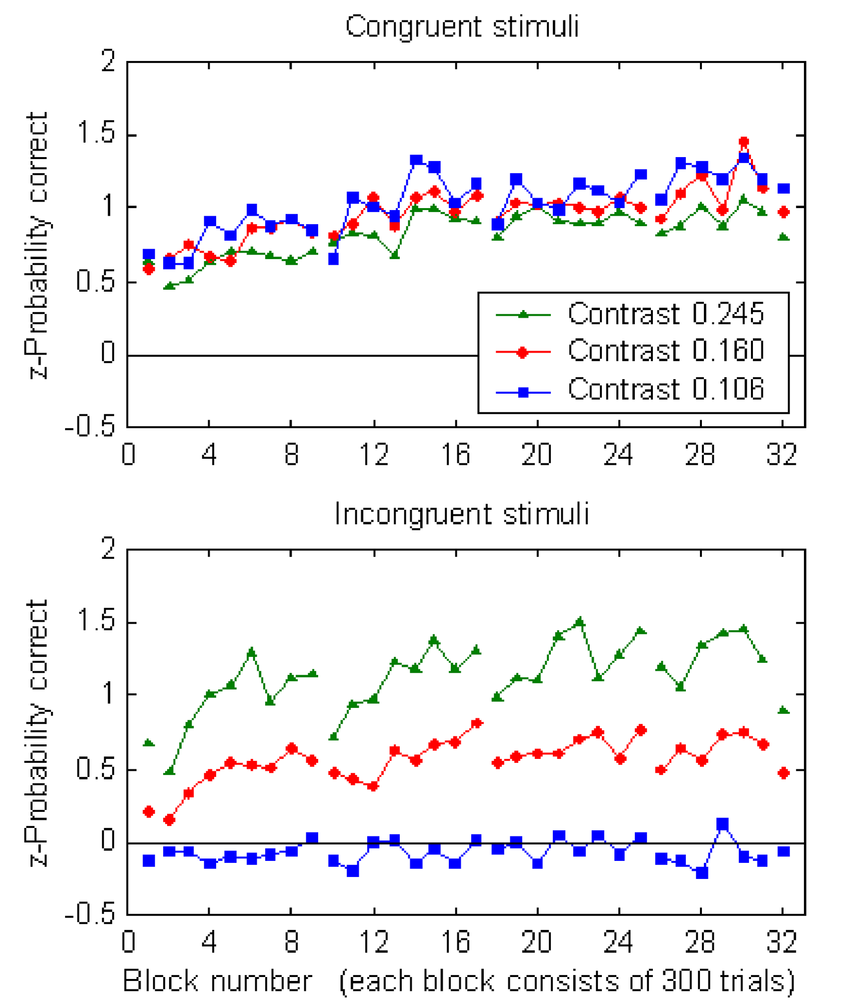
Learning curves for the three target contrast levels




The three learning curves seem to have identical dynamics: a "main" component that depends only on the global time $T$ and a superimposed "switch cost" that depends only on the time since last context switch $t_s$. The two components have different time constants: τ=10 and $\tau_s$=1.2 blocks, respectively. The initial $d'$ for each Gabor contrast is approximately one-half ($g$=0.47) of the corresponding asymptote: $D_{0.245}$=1.2, $D_{0.160}$=1.9, $D_{0.106}$=2.4.

$$d'(T,t_s) = D\,(\underbrace{1 - g\,e^{-T/\tau}}_{\text{Main component}} \underbrace{- s\,e^{-t_s/\tau_s}}_{\text{Switch cost}})$$

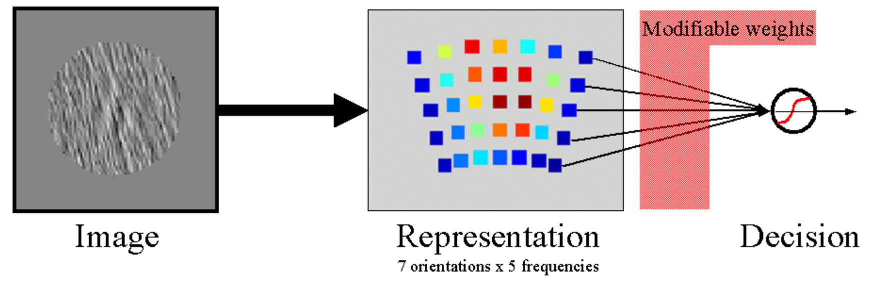
Importantly, each switch of the background context incurs a temporary decrement in performance. The magnitude of this "switch cost" is approximately 40% of the overall learning effect ($s$=0.18=0.40$g$) and does not seem to diminish even after 9600 trials and 5 consecutive switches.
This persistent, context-induced switch cost cannot be accounted for by the representation enhancement hypothesis.




For context-congruent targets, accuracy (*z*-transformed probability correct) paradoxically *decreases* slightly with increasing Gabor contrast; for incongruent targets, it increases substantially with Gabor contrast.

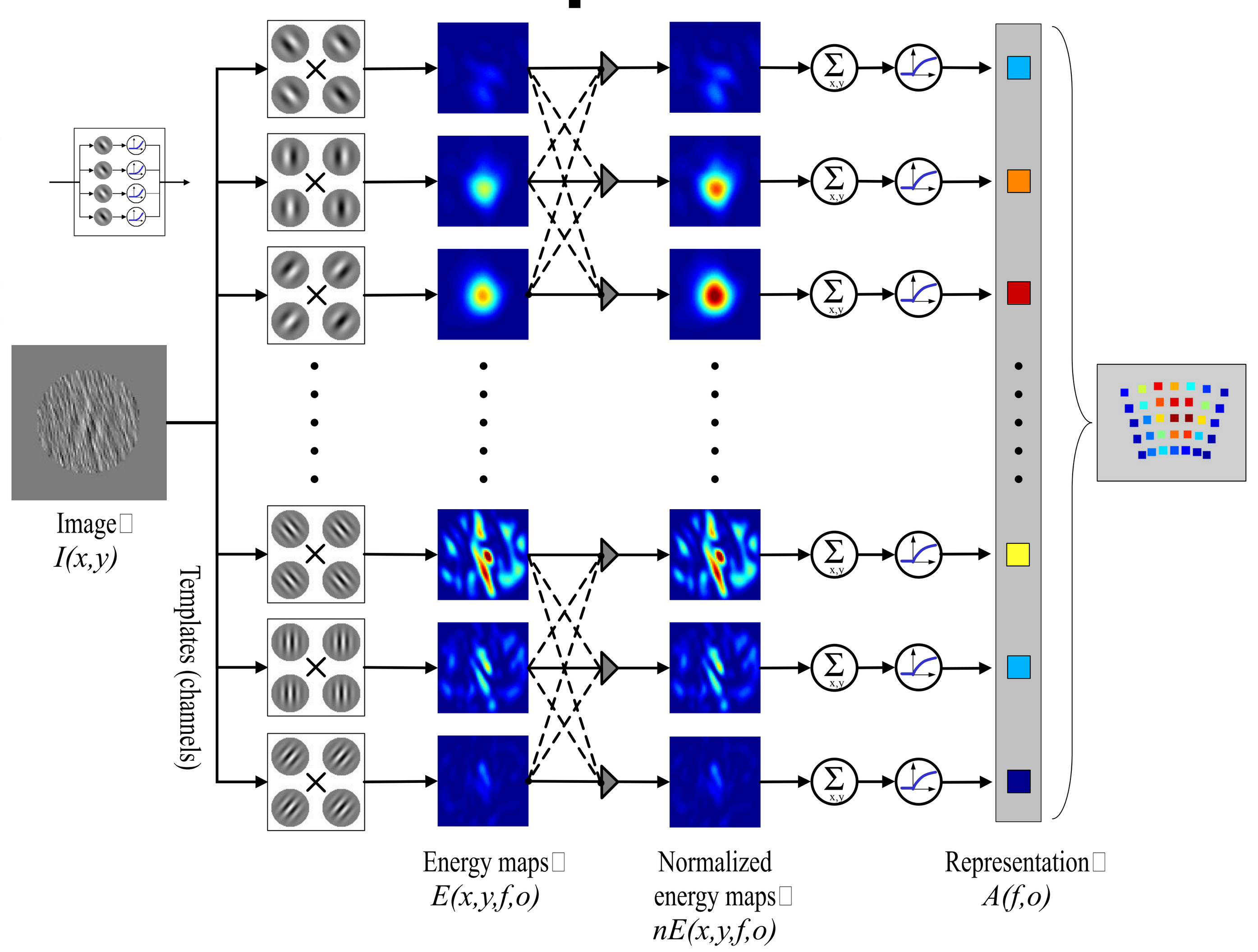
## Model Principles

* **Orientation- and Frequency-Selective Representations.** Visual images are represented as patterns of activity over a population of *representational units* tuned for orientation and spatial frequency.
* **Contrast Gain Control.** Due to lateral and/or shunting inhibition, the activations of the units are interdependent and vary as saturating non-linear functions of the stimulus contrast (Heeger, 1992).
* **Weighted decision units.** The response ("Left" or "Right") is determined by a population of decision units. Each decision unit receives inputs, directly or indirectly, from the representational units. The *effective weight* of each representational unit measures the strength of its influence on a given decision unit.
* **Incremental Error-Driven Re-weighting.** Perceptual learning occurs through changes in the effective weights of the connections (direct or indirect) between the representational and decision units (Dosher & Lu, 1998). Thus, learning can be both stimulus- and task-specific. All changes are incremental and tend to reduce the discrepancy between the stimulus-induced and the task-prescribed activations over the decision units.
* **Intrinsic variability.** The processing units throughout the system are noisy and prone to various inefficiencies and fluctuations.

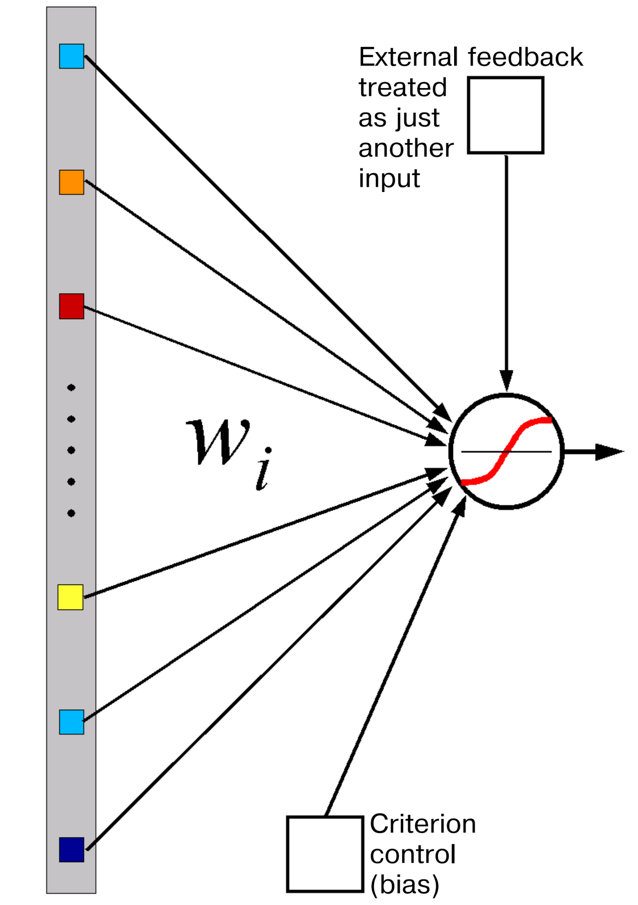



The model takes grayscale images as inputs and produces binary responses as outputs. It is implemented as two separate parts as indicated in the Figure above. The *representation subsystem* computes the internal representation of the input image. It is implemented in MATLAB and produces a matrix of 7x5 activations encoding the (normalized) energy at selected orientations and frequencies. The tuning properties of the individual representational elements (or "channels") are informed by the neurophysiology of the early visual areas.
The model is intended as an existence proof that the selective reweighting hypothesis is sufficient to account for all patterns in our data set, including the trial-by-trial dynamics of learning, the persistent switch costs, and the congruence effects. The internal representations do not change at all. All learning happens via selective reweighting of the "read-out" connections highlighted in the Figure.
The *learning and decision-making subsystem* is implemented as a single-layer perceptron, which is a simple instantiation of the general principles above. The weights are updated by a biologically plausible error-correcting learning rule.

## Internal Representations




## Error-Driven Learning



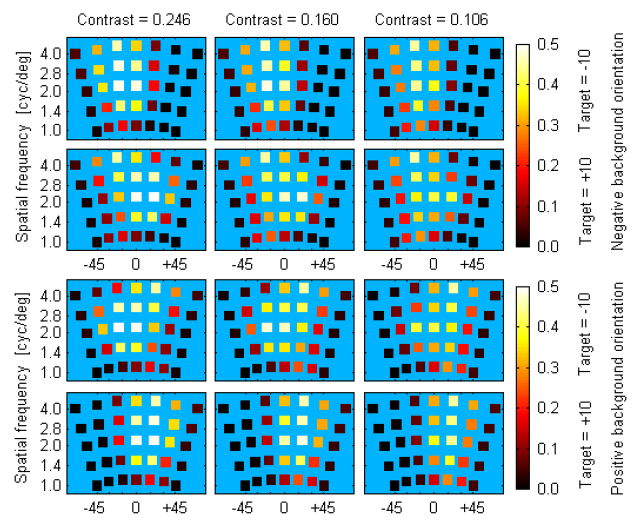

All information contained in the stimulus representation converges on the decision unit. Prior knowledge is encoded in the initial weight vector: $w$=–0.16 and +0.16 for all "left" and "right" orientations, respectively. Given that the Gabor target activates a restricted frequency band, not all representation units are equally predictive of the correct response as indicated by the feedback. The identification accuracy can be improved by increasing the weights of the task-correlated units and decreasing the weights of the uncorrelated ones. This is accomplished incrementally by the *contrastive Hebbian learning rule:*

$$\Delta_i = a_i o^+ - a_i o^-$$

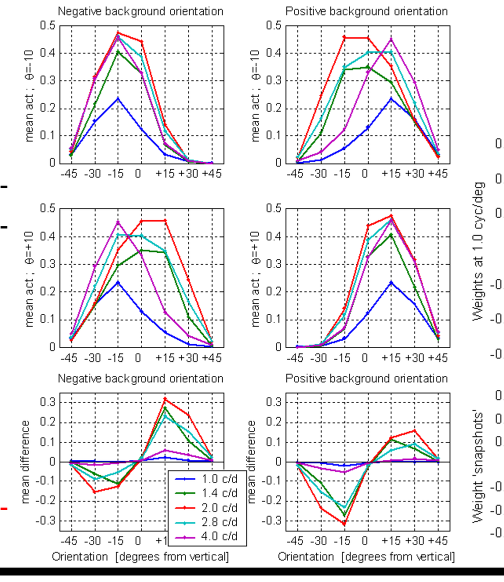
$$\Delta w_i \sim [\Delta_i]_+ (1 - w_i) + [\Delta_i]_- (w_i + 1)$$

The *error* on a trial is estimated by the difference $(o^+ - o^-)$, where $o^-$ and $o^+$ are the activation levels of the decision unit before and after feedback is provided, respectively. The weights are then updated in the direction that reduces the error. The magnitude of the change $\Delta w_i$ of each individual weight is scaled by the activation $a_i$ of the corresponding representation unit. This can be accomplished in a biologically plausible way by a sequence of Hebbian and anti-Hebbian updates according to the first equation above.
*Soft weight bounding* ensures that all weights remain between –1 and +1 (O'Reilly & Munakata, 2000).

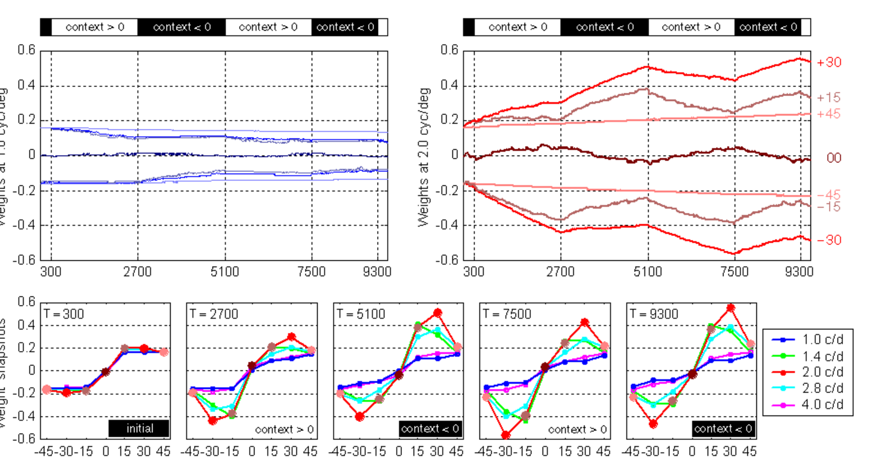
## Task Analysis



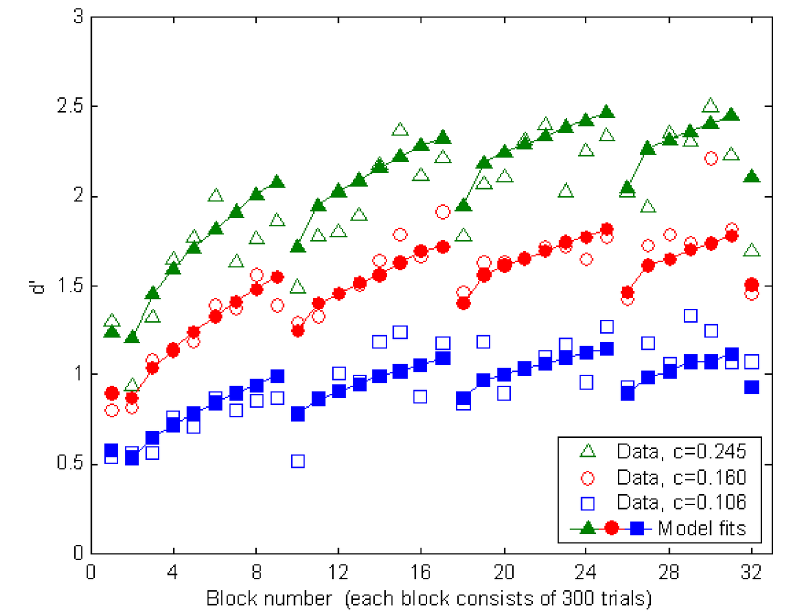

The learning algorithm tracks the correlations between the representation units and the desired output. An approximate way to estimate these correlations is to average the representations of all "left" stimuli (top two panels in the Figure) and subtract it from the average of all "right" stimuli (middle panels).
The channels clobbered by the background noise are less predictive than their counterparts across the midline. This leads to "off-channel looking" and explains the inverse relationship between contrast and accuracy for congruent stimuli. Moreover, the optimal weight vectors in the two contexts are not the same. This asymmetry causes persistent switch costs as weights optimized in one background must be re-optimized in the other.

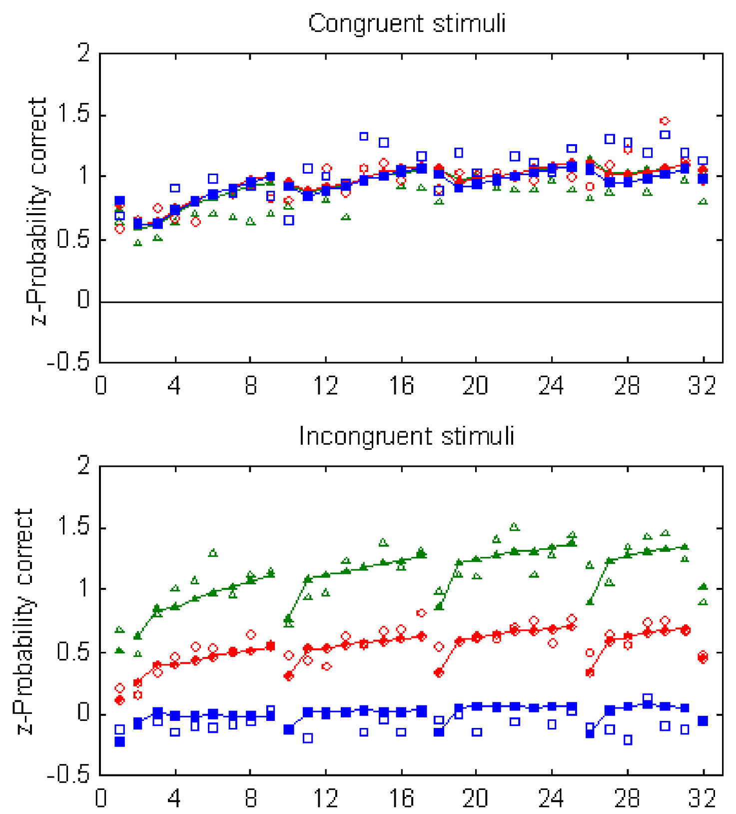



## Weight Dynamics




## Model Fits




## Criterion Control

The incremental errror-correcting algorithm predicts the intermediate- and long-term dynamics of perceptual learning very well. It accounts for the gradual improvement over the course of days and for the switch costs over the course of blocks. It also accounts for the absolute discriminability levels at all target contrasts and for the counterintuitive contrast-by-congruence interaction.
The $d'$ levels are determined by the signal-to-noise ratios, which in turn are determined by the relative weighting of the representational features. The error-correcting mechanism outlined above is necessary and sufficient to reproduce all $d'$ profiles in the data. It cannot, however, account for the rapid strategically guided criterion control suggested by the *z*-probability profiles.
The model has a mechanism for explicit criterion control that avoids excessive disproportions in the response frequencies. The model maintains an exponentially discounted running average of its previous responses, counting "Left" as –1 and "Right" as +1, respectively. If the average deviates too far from zero in either direction, it triggers a correction of the decision criterion. For consistency, it also introduces a slight asymmetry in the teaching signal.
To illustrate, suppose the context has just switched from *R* to *L*. The model generates a short sequence of predominantly "Left" responses. This triggers an abrupt resetting of the decision criterion to a predefined negative value, thereby facilitating the "Right" response and equilibrating the response frequencies.

## Conclusions

Perceptual learning is investigated both experimentally and via a detailed mechanistic model. The stimuli and the task remain fixed at all times. Non-stationary contexts and multiple contrast levels generate a rich set of empirical constraints.
The performance gradually improves with practice, with context-induced switch costs that persist for at least 5 switches and 9600 trials. For congruent stimuli, accuracy paradoxically decreases slightly with increasing Gabor contrast.
A computational model accounts for all these results. It is broadly consistent with the neurophysiology of the early visual areas. The stimuli are represented as contrast-normalized patterns of activity over a population of orientation and frequency tuned units. In a stong test of the selective reweighting hypothesis, the representations are fixed at all times (Dosher & Lu, 1998). Learning occurs only in the "read-out" links to the decision unit by an incremental error-correcting algorithm.
Task-correlated units gain strength while irrelevant frequencies and orientations are suppressed, producing a gradual learning curve. The optimal weight vectors discount the noisy channels in each context ("off-channel looking"). If the background shifts abruptly, the system suffers a switch cost as it works with suboptimal weights until it readapts. The cost is transient but appears consistently after each switch.

### Acknowledgement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