Vision Research 50 (2010) 375–390

Contents lists available at ScienceDirect

Vision Research

journal homepage: www.elsevier.com/locate/visres

Modeling mechanisms of perceptual learning with augmented Hebbian re-weighting

Zhong-Lin Lu [a,*], Jiajuan Liu [b], Barbara Anne Dosher [c]

[a] Laboratory of Brain Processes (LOBES), Dana and David Dornsife Cognitive Neuroscience Imaging Center, Department of Psychology, University of Southern California, Los Angeles, CA 90089-1061, United States

[b] Neuroscience Graduate Program, Department of Biological Sciences, University of Southern California, Los Angeles, CA 90089-2520, United States

[c] Memory, Attention and Perception Laboratory (MAPL), Department of Cognitive Sciences and Institute of Mathematical Behavioral Sciences, University of California, Irvine, CA 92697-5100, United States

ARTICLE INFO

Article history:
Received 31 March 2009
Received in revised form 27 August 2009

Keywords:
Re-weighting
Hebbian learning
Stimulus enhancement
External noise exclusion
Mechanisms of perceptual learning

ABSTRACT

Using the external noise plus training paradigm, we have consistently found that two independent mechanisms, stimulus enhancement and external noise exclusion, support perceptual learning in a range of tasks. Here, we show that re-weighting of stable early sensory representations through Hebbian learning (Petrov et al., 2005, 2006) can generate performance patterns that parallel a large range of empirical data: (1) perceptual learning reduced contrast thresholds at all levels of external noise in peripheral orientation identification (Dosher & Lu, 1998, 1999), (2) training with low noise exemplars transferred to performance in high noise, while training with exemplars embedded in high external noise transferred little to performance in low noise (Dosher & Lu, 2005), and (3) pre-training in high external noise only reduced subsequent learning in high external noise, whereas pre-training in zero external noise left very little additional learning in all the external noise conditions (Lu et al., 2006). In the augmented Hebbian re-weighting model (AHRM), perceptual learning strengthens or maintains the connections between the most closely tuned visual channels and a learned categorization structure, while it prunes or reduces inputs from task-irrelevant channels. Reducing the weights on irrelevant channels reduces the contributions of external noise and additive internal noise. Manifestation of stimulus enhancement or external noise exclusion depends on the initial state of internal noise and connection weights in the beginning of a learning task. Both mechanisms reflect re-weighting of stable early sensory representations.

1. Introduction

Perceptual learning—performance improvements through training or practice in perceptual tasks—has been documented over a wide range of tasks in all sensory modalities (Fahle & Poggio, 2002). Many studies on perceptual learning have focused on the specificity or transfer of perceptual learning to assess the functional locus of learning (Ahissar & Hochstein, 1996; Ball & Sekuler, 1982; Fahle & Edelman, 1993; Fiorentini & Berardi, 1980; Karni & Sagi, 1991; Liu & Vaina, 1998; Poggio, Fahle, & Edelman, 1992; Seitz, Kim, & Shams, 2006; Shiu & Pashler, 1992; Vogels & Orban, 1985; Xiao et al., 2008). Increasingly, there is also interest in understanding the mechanisms of perceptual learning, that is, what is learned during perceptual learning (Chung, Levi, & Tjan, 2005; Crist, Li, & Gilbert, 2001; Dosher & Lu, 1998, 1999; Fahle & Daum, 2002; Ghose, Yang, & Maunsell, 2002; Gold, Bennett, & Sekuler, 1999; Law & Gold, 2008; Lu et al., 2008; Saarinen & Levi, 1995; Schiltz et al., 1999; Schoups, Vogels, Qian, & Orban, 2001; Schwartz, Maquet, & Frith, 2002; Seitz et al., 2006). Understanding the mechanisms of perceptual learning may provide insights into the nature of plasticity in the adult brain, and may also have profound implications for remediation of perceptual functions in clinical populations (Huang, Zhou, & Lu, 2008; Levi & Li, 2009; Polat, Ma-Naim, Belkin, & Sagi, 2004; Zhou et al., 2006).

Motivated by principles in signal processing and neurophysiology, we developed the external noise plus attention/training paradigm and a theoretical framework based on the perceptual template model (PTM; Fig. 1a) to distinguish mechanisms of attention and perceptual learning (Dosher & Lu, 1998; Lu & Dosher, 1998; see Lu and Dosher (2008) for a recent review). In this approach, perceptual inefficiencies are attributed to three limitations in perceptual processes: imperfect perceptual template(s), internal additive noise, and multiplicative noise. System-

* Corresponding author. Address: Laboratory of Brain Processes (LOBES), Dana and David Dornsife Cognitive Neuroscience Imaging Center, Department of Psychology, University of Southern California, Los Angeles, CA 90089-1061, United States. Fax: +1 213 746 9082.

E-mail address: zhonglin@usc.edu (Z.-L. Lu).

0042-6989/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.visres.2009.08.027

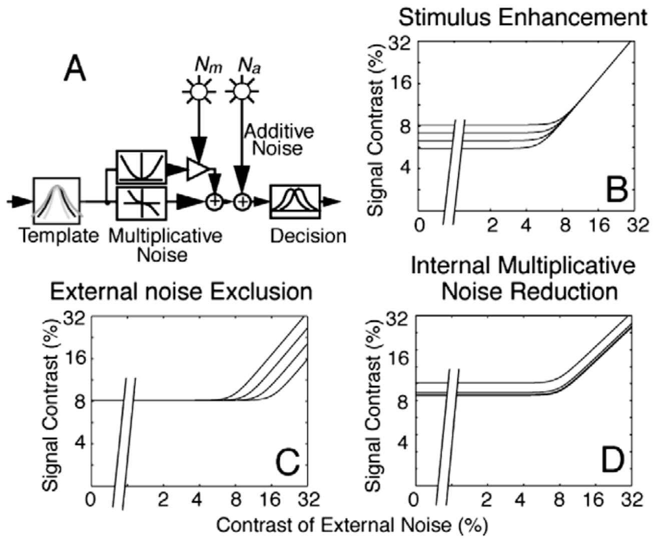

Fig. 1. (A) Schematics of the perceptual learning model (PTM). (B) Stimulus enhancement improves performance at low and zero external noise. (C) External noise exclusion improves performance only at high levels of external noise. (D) Internal multiplicative noise improves performance at all levels of external noise, but slightly more so as external noise increases.

atic measurements of human performance as a function of both the amount of external noise added to the signal stimulus and training received by the observers enable us to analyze how perceptual inefficiencies improve over the course of perceptual learning and therefore identify mechanisms of perceptual learning. There are three potential mechanisms. *Stimulus enhancement* increases the gain to both the signal and external noise in the stimulus and is associated with reduction of absolute threshold and performance improvements in the absence or presence of low external noise (Fig. 1b). *External noise exclusion* improves the perceptual template(s) to exclude external noise and is associated with performance improvements only in the presence of high external noise (Fig. 1c). *Internal multiplicative noise (or gain control) reduction* increases system response to stimulus contrast and is associated with improvements throughout the full range of external noise levels (Fig. 1d). Measurements of performance at multiple criterion performance levels (a proxy for full psychometric functions) throughout the course of perceptual learning are necessary to distinguish pure mechanisms and mechanism mixtures (Dosher & Lu, 1999).

In the first application of the external noise plus training paradigm, Dosher and Lu (1998, 1999) investigated mechanisms of perceptual learning in an orientation identification task in the periphery. Virtually identical magnitudes of performance improvements (contrast threshold reduction) were observed at two performance levels. They concluded that the mechanism of perceptual learning consists of a mixture of stimulus enhancement and external noise exclusion rather than multiplicative noise reduction. Essentially the same pattern of results was observed by Gold et al. (1999) at a single performance level in a face identification task, although they came to a different interpretation (see Lu and Dosher (2009) for detailed discussion). Mixtures of stimulus enhancement and external noise exclusion have been reported in other tasks (Lu, Chu, Dosher, & Lee, 2005; Lu, Chu, & Dosher, 2006).

Two additional studies tested the separability of stimulus enhancement and external noise exclusion (Dosher & Lu, 2005; Lu et al., 2006). Using an orientation identification task similar to Dosher and Lu (1998, 1999), Dosher and Lu (2005) found that training in a simple Gabor orientation identification task exhibited an asymmetric pattern of transfer. Training with low noise exemplars transferred to performance in high noise, while training with high noise exemplars – in which target objects were embedded in white external noise – transferred little to performance in low noise. In the other study, Lu et al. (2006) trained their observers in a motion direction identification task in fovea. They found that: (1) Without pre-training, perceptual learning significantly reduced contrast thresholds by about the same amount across all the external noise levels. (2) Pre-training in either zero or high external noise condition significantly reduced contrast thresholds in the corresponding external noise condition. (3) Pre-training in high external noise greatly reduced subsequent learning in high external noise but left subsequent learning in low external noise essentially intact. (4) Pre-training in zero external noise left only little residual learning in all the external noise conditions. To explain the asymmetric pattern of transfer of perceptual learning in clear and noisy displays and different effects of pre-training in low and high external noise conditions, Dosher and Lu (2005) and Lu et al. (2006) hypothesized that (1) the two mechanisms of perceptual learning, external noise exclusion and stimulus enhancement, are independent, and (2) whereas training in high external noise could only improve external noise exclusion, training in zero external noise may substantially improve external noise exclusion and enhance the stimulus.

Based on the results of their initial external noise study on perceptual learning and existing results in the literature, Dosher and Lu (1998) postulated the re-weighting hypothesis in perceptual learning: "perceptual learning primarily serves to select or strengthen the appropriate channel and prune or reduce inputs from irrelevant channels. The connections between the most closely tuned visual channel and a learned categorization structure are maintained or strengthened, while input from other channels is reduced or eliminated." This claim was also consistent with an earlier commentary made by Mollon and Danilova (1996). Although the re-weighting hypothesis was first outlined in the context of an external noise study of perceptual learning, its focus on the architecture and process of perceptual learning is quite different from that of the external noise/mechanisms studies, which primarily focus on the impact of perceptual learning on intrinsic limitations of perceptual processes. Whether and how channel re-weighting can lead to the various observed patterns of results in the empirical external noise studies on perceptual learning needs to be evaluated. The current study is our first computational investigation of the re-weighting hypothesis in relation to the empirical studies on perceptual learning that explicitly manipulated the amount of external noise.

Our investigation is based on the Augmented Hebbian Re-weighting Model (AHRM) developed by Petrov, Dosher & Lu, (2005). The model is a full multi-channel implementation of the channel re-weighting hypothesis outlined in Dosher and Lu (1998). Originally, the AHRM was developed to provide a computational instantiation of the re-weighting hypothesis and to model the detailed learning dynamics and recurring switch costs of perceptual learning in non-stationary contexts (Petrov et al., 2005). It has since been used to model perceptual learning in non-stationary contexts with and without feedback (Petrov, Dosher & Lu, 2006), interactions between feedback and training accuracy (Liu, Lu, & Dosher, 2008), and the Eureka effect in perceptual learning (Ahissar & Hochstein, 1997, Liu, Lu, & Dosher, 2009; Rubin, Nakayama, & Shapley, 1997). These previous applications all involved tests in high external noise, but did not address the mechanisms of perceptual learning in different external noise environments. In this study, we test the AHRM against empirical results on mechanisms of perceptual learning by applying the AHRM to data from experiments in which external noise was explicitly manipulated. Data from Dosher and Lu (1998, 1999, 2005), and Lu et al. (2006) are considered.