



Learning optimal eye movements to unusual faces



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ABSTRACT

Eye movements, which guide the fovea's high resolution and computational power to relevant areas of the visual scene, are integral to efficient, successful completion of many visual tasks. How humans modify their eye movements through experience with their perceptual environments, and its functional role in learning new tasks, has not been fully investigated. Here, we used a face identification task where only the mouth discriminated exemplars to assess if, how, and when eye movement modulation may mediate learning. By interleaving trials of unconstrained eye movements with trials of forced fixation, we attempted to separate the contributions of eye movements and covert mechanisms to performance improvements. Without instruction, a majority of observers substantially increased accuracy and learned to direct their initial eye movements towards the optimal fixation point. The proximity of an observer's default face identification eye movement behavior to the new optimal fixation point and the observer's peripheral processing ability were predictive of performance gains and eye movement learning. After practice in a subsequent condition in which observers were directed to fixate different locations along the face, including the relevant mouth region, all observers learned to make eye movements to the optimal fixation point. In this fully learned state, augmented fixation strategy accounted for 43% of total efficiency improvements while covert mechanisms accounted for the remaining 57%. The findings suggest a critical role for eye movement planning to perceptual learning, and elucidate factors that can predict when and how well an observer can learn a new task with unusual exemplars.

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1. Introduction

Perceptual learning, whereby training leads to significant and sustained improvement in perceptual tasks, has been studied at the behavioral and neural level for many years (Fine & Jacobs, 2002; Gilbert, Sigman, & Crist, 2001; Goldstone, 1998). The brain's ability to improve perceptual performance across a wide range of modalities (visual: Ahissar & Hochstein, 1993; Fiorentini & Berardi, 1980; Matthews et al., 1999; auditory: Atienza, Cantero, & Dominguez-Marín, 2002; Polley, Steinberg, & Merzenich, 2006; olfactory: Moreno et al., 2009; Wilson & Stevenson, 2003; somatosensory: Pleger et al., 2003; Sathian & Zangaladze, 1998) and tasks (motion discrimination: Ball & Sekuler, 1982, 1987; texture segregation: Karni & Sagi, 1991, 1993; auditory frequency discrimination: Hawkey, Amitay, & Moore, 2004; wine discrimination: Bende & Nordin, 1997) suggests that learning is mediated by a complex and, at some level, generalized set of neural mechanisms and corresponding behaviors. Focusing on visual learning, past research has implicated modulations at the neural and algorithmic levels, such as internal noise reduction (Doshier & Lu, 1998; Lu &

Doshier, 1998), signal amplification (Gold, Bennett, & Sekuler, 1999; Lu & Doshier, 1999), feature/receptive field tuning (Li, Levi, & Klein, 2004; Saarinen & Levi, 1995), and attentional reallocation (Ahissar & Hochstein, 1993; Gilbert, Sigman, & Crist, 2001; Ito, Westheimer, & Gilbert, 1998; Peterson, Abbey, & Eckstein, 2009; Trenti, Barraza, & Eckstein, 2010). Common to many of these mechanisms is the fundamental concept of improved efficiency at selecting, processing, and integrating task-relevant information or features (Beard & Ahumada, 1999; Doshier & Lu, 1998; Eckstein et al., 2004; Gold, Bennett, & Sekuler, 1999; Hurlbert, 2000; Peterson & Eckstein, 2012).

Although these studies have increased our understanding of the mechanisms mediating perceptual learning, most investigations have not considered the role active vision, and specifically eye movements, plays in perceptual learning (but see Chukoskie et al., 2013; Droll, Abbey, & Eckstein, 2009; Holm, Engel, & Schrater, 2012 for exceptions). This would seem to be an important factor to explore, as the inhomogeneity in visual of processing across the visual field suggests that during active vision, familiarization with a perceptual environment might lead to changes in saccade strategies and contribute to performance improvements. While the physical world surrounds us across all angles, the visual system is limited to a slightly greater than 180° field of view at any given time, with only a tiny portion of this area surrounding

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fixation (corresponding to the fovea) given access to high-resolution, high-sensitivity processing. This architecture creates a need for the brain to intelligently guide the eyes through head, body, and eye movements such that task-relevant information, in the form of light, impinges areas of the retina that correspond to high-powered processing by visual cortex. The critical role that eye movement behavior plays in perception can be seen in such common but important tasks as visual search (Eckstein et al., 2007; Hayhoe & Ballard, 2005; Najemnik & Geisler, 2005, 2009; Rao et al., 2002; Tavassoli et al., 2009; Zelinsky et al., 1997), reading (Rayner, 1998), and face recognition (Blais et al., 2008; Hsiao & Cottrell, 2008; Peterson & Eckstein, 2012). Indeed, humans display a remarkable ability to enact eye movement strategies that are consistent with optimal fixation model predictions (Najemnik & Geisler, 2005, 2008; Peterson & Eckstein, 2012). Given the vital nature of this interaction, surprisingly little work has assessed the functional role of eye movement strategy modulation to perceptual learning beyond that conferred by modification to covert mechanisms, and how the brain learns these strategies.

Here, we assess how practice changes observers' eye movement strategies and evaluate their functional role in performance improvements. We chose a task, face identification, for which humans have already learned optimized eye movement strategies to typical, naturally occurring faces (Peterson & Eckstein, 2012). We constructed face images where all discriminatory information was confined to a small region encompassing the mouth, creating a situation where the optimal eye movement strategy for this synthetic face set diverged greatly from the optimal strategy for normal faces. Without any special instructions, observers were asked to identify these faces over the course of 1600 trials. We measured changes in fixation patterns and isolated the contribution to accuracy improvements due to eye movement modulations by interleaving trials where eye movements were allowed with trials where fixation was confined to a specific region. We found that observers fell into three distinct groups defined by their eye movement modulation: Non Movers, Partial Movers, and Complete Movers. Adapting fixation strategy was found to significantly increase performance beyond that possible with only modulations to covert mechanisms. The magnitude of overall improvement, and the ability of observers to modify their eye movements without instruction, was seen to be influenced mainly by two factors: (1) The distance of the observer's initial, normal fixation region from the new optimal location, and (2) The observer's peripheral processing ability. We conclude that eye movements can be an essential element in maximizing learning of new perceptual tasks, and that the ability to learn these new strategies can be predicted by the observer's ability to notice and process task-relevant information across the visual field.

2. General methods

2.1. Participants

Fourteen undergraduate students (eight female, six male, age range 20–23) from the University of California, Santa Barbara participated in the study for course credit. All observers had normal or corrected-to-normal vision and no history of neurological disorders. Each observer completed all four tasks.

2.2. Display

All stimuli were presented using a linearly calibrated 17-in. CRT monitor set to 8-bit grayscale with mean luminance of 25 cd/m², resolution of 600 by 800 pixels, and refresh rate of 100 Hz. Observers sat 63 cm from the monitor, with each pixel subtending .037° visual angle.

2.3. Eye tracking

The left eye of each participant was tracked using an SR Research Eyelink 1000 Tower Mount eye tracker sampling at 250 Hz. A nine-point calibration and validation were run before each 100 trial session with a mean error of no more than 0.5° visual angle. Using Eyelink's suggested criteria, saccades were classified as events where eye velocity was greater than 22°/s and eye acceleration exceeded 4000°/s². Periods of forced fixation were enforced by aborting the current trial if the eye position registered more than 1° from the center of the fixation cross.

2.4. Procedure

The entire study consisted of four distinct sections, each of which is described in detail in Sections 3–6. In general, grayscale face images were randomly selected from a small set of possible images and briefly shown to observers with additive Gaussian white noise. Observers were then presented with high contrast, noise-free versions of the possible face images and used the mouse to click on the face they thought they had seen.

2.5. Ideal observer, efficiency, and the learning factor

Performance is dictated by an interaction between the visual information available for a task and the visual system's ability to extract and process this information. The amount of task-relevant information can be assessed using ideal observer theory, a technique that specifies an algorithm that makes Bayesian optimal decisions given the statistical properties of the possible signals (here, face images) and the added stochastic noise (Green, 1966). The ideal observer provides a gold standard for maximum task performance. Human behavior and its associated performance are thus conceptualized as the result of some noisy process (the visual system) that incorporates only a portion of the available information into its decisions. This proportion is quantified with the absolute efficiency metric, η , which is defined as the ratio of the ideal observer's signal contrast energy, $E_{IO|human}$, to that of the human's, E_{human} , for a given performance threshold (Barlow, 1980; Burgess et al., 1981; Eckstein et al., 2004). Here, the signal is the original face image, which is common to both the ideal observer and the humans and whose contrast energy is designated by E_0 . The signal was then modified using a contrast multiplier (a scalar value between 0 and 1 that attenuates signal strength and thus decreases stimulus information), denoted as C_{human} for the psychophysical trials (kept constant across trials and observers) and $C_{IO|human}$ for the ideal observer, where the ideal observer's multiplier value was chosen so as to match the human's perceptual accuracy. Thus, the total contrast energy is the original signal's contrast energy multiplied by the square of the contrast multiplier. Using these properties, the absolute efficiency is computed as:

$$\eta = \frac{E_{IO|human}}{E_{human}} = \left(\frac{C_{IO|human} E_0}{C_{human} E_0} \right)^2 = \left(\frac{C_{IO|human}}{C_{human}} \right)^2 \quad (2.5.1)$$

Efficiency is a monotonic transform of human performance: improvement in an observer's proportion correct, the most classic behavioral trademark of learning, directly translates to increased efficiency. Efficiency formalizes this learning in terms of the increase in the amount of task-relevant information the observer is able to incorporate into the perceptual decision.

In this study, we measured learning in two conditions: when eye movements were allowed (*free*) and when fixation was constrained to a specific location (*fixed*), with these trial types run in an interleaved fashion. For any given condition, c , and time frame of interest, t , the total amount of learning, $\Delta\eta_{c,t}$, is given by the

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