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Introduction to Special Issue on Perceptual Learning

In memory of our friend and colleague, Bosco Tjan

Almost 40 years after classic papers (Ball & Sekuler, 1982; Fiorentini & Berardi, 1980; McKee & Westheimer, 1978) that triggered a wave of research on perceptual learning, the field remains vibrant and relevant. Rehabilitation for humans with visual impairments (Legge & Chung, 2016) associated with amblyopia (Levi & Li, 2009; Lu, Lin, & Dosher, 2016; Polat, Ma-Naim, Belkin, & Sagi, 2004), macular degeneration (Janssen & Verghese, 2016; Plank et al. 2014), strokes (Melnick, Tadin, & Huxlin, 2016) and age-related presbyopia (Deveau & Seitz, 2014; Polat et al., 2012) is critically important. Understanding how perceptual learning generalizes or transfers to new locations or stimuli remains an important focus in the field (Green, Kattner, Siegel, Kersten, & Schrater, 2015), with new research investigating transfer across sensory modalities (McGovern, Astle, Clavin, & Newell, 2016), as well as investigating computational approaches (Dosher, Jeter, Liu, & Lu, 2013). The interaction between perceptual learning and other cognitive functions, such as attention (Ni, Ruff, Alberts, Symmonds, & Cohen, 2018; Szpiro & Carrasco, 2015), eye movements (Kwon, Nandy, & Tjan, 2013; Szpiro & Carrasco, 2015; Tsank & Eckstein, 2017), and category learning (Cantwell, Riesenhuber, Roeder, & Ashby, 2017; Carvalho & Goldstone, 2016; Rosedahl, Eckstein, & Ashby, 2018), is an increasing area of research focus. Such efforts will help place perceptual learning in more ecologically valid contexts and help us understand the common mechanisms involved in other visuo-cognitive functions. This special issue follows the 5th International Workshop on Perceptual Learning organized in Patagonia, Argentina. The papers in the issue comprise of work presented at the workshop and additional independent contributions submitted in response to the call for papers. Together, the work in this issue advances the field along traditional questions in perceptual learning and expands the field in new directions. The papers can be grouped into three main themes: (1) the classic theme of specificity vs. generalization (transfer) of learning; (2) psychophysical training to overcome visual deficits; and (3) interactions of perceptual learning with other cognitive and motor functions.

1. Specificity vs. Generalization of Perceptual Learning

Determining when perceptual improvement generalizes across stimulus properties or retinal locations, commonly referred to as transfer, has been central to the field of perceptual learning (Karni & Sagi, 1991; Watanabe & Sasaki, 2015). Understanding such a process can uncover the particular mechanisms and algorithms that not only manifest transfer of learning in contrast to specificity but are also critical to training protocols that aim to instill learning that is not constrained to a particular stimulus or location on the retina. Four papers in this issue spanning visual, tactile, and motor learning relate to this research area.

One of the techniques that elicits transfer across locations is the training protocol referred to as double training (Xiao et al. 2008). In this method, the new location is either trained with a secondary task or the first location is trained with a wider set of stimulus properties such as orientation or contrast. Yet, it is unknown whether the mechanism by which the improvement occurs at the training and transfer locations is the same. In their paper, Xie and Yu use the external noise paradigm to measure contrast thresholds as a function of noise magnitude to evaluate which of various possible candidate mechanisms mediate the learning. They find that the improvement in performance with learning can be interpreted as an increase in sampling efficiency or a combination of internal noise reduction and external noise exclusion. Critically, the mechanisms seem to be the same at the trained and transfer locations. What type of algorithmic architecture predicts when human learning will generalize? Stopoulopulus et al. propose a computational model that can predict when learning will generalize. They expand on the integrated re-weighting model (Dosher et al., 2013) to include a dynamic weighting of retinotopic-location-specific vs. location independent representations based on internal performance estimates of the two representations. This expanded model allows the authors to predict a variety of psychophysical data on the transfer of perceptual learning, including double training and the interactions with the trial-length of an adaptive threshold method (staircase procedure).

Willey and Liu extend classic work on the effect of variability during practice in enhancing generalization of learned skills. The work is in the domain of motor programs, following a paradigm from classic work by Kerr and Booth (1978). They assessed how motor errors, when throwing beanbags to specific targets, diminished with small perturbations (1 foot) in the target location during training. Willey and Liu expanded on the original study by investigating various distances from the target to the thrower. They found some support for the finding that training subjects with variability in target locations results in higher generalization of the learning, but found that the advantage was mainly present for the longest distance and disappeared by a post-test given two weeks after the 5-7 weeks of practice.

Arnold and Auvray also study how generalization of learning interacts with stimulus variability and task difficulty during training. The authors investigate the question in the domain of tactile representations of visual stimuli. Sensory substitution devices transform stimuli from one modality to another (e.g. visual to tactile) and are intended to aid humans with a deficient sensory modality. In their paper, they focus on the learning of alphanumerical tactile stimuli. They show that with a small set of stimuli, the learning is specific and does not generalize to new alphanumerical stimuli. In contrast, larger stimuli sets with increasing feature variability and task difficulty generalized to newer alphanumerical stimuli and orientations.

Together, the papers emphasize that the finding that stimuli variability during training leads to greater generalization of learning is a phenomenon that is not specific to visual sensory modalities, but also extends to motor and tactile modalities. The papers also help specify some of the mechanisms and computational architecture mediating the transfer of the learning.

2. Psychophysical training to overcome visual deficits

How to best design training methods to achieve significant and persistent perceptual improvements that generalize to real world tasks is fundamental for the establishment of psychophysical rehabilitation techniques for humans with visual deficits. Yu and colleagues focus on the problem of slow reading with peripheral vision, which is a limitation for humans who suffer central field loss. They aim to increase the speed of reading in the visual periphery by utilizing a letter-recognition training method that adaptively shortens the time of presentation of the letters in the visual periphery. They utilized normally sighted individuals and showed that training letter recognition at a given eccentricity (10 degrees in the lower visual field) led to faster reading that generalized to various eccentricities and across different visual fields. The adaptive time procedure has an advantage over a fixed stimulus presentation method in that it can be better tailored to individual patients.

Sterkin and colleagues study the impact of utilizing structured and personalized perceptual learning methods to compensate for age-related deterioration in near vision (presbyopia). They conduct their study with airplane military pilots for whom near visual acuity is essential to monitor control and performance instruments in the cockpit. They show that utilizing a training method with low contrast Gabor stimuli from a distance of 40 cm results in robust improvements across a variety of basic visual tasks including static and temporal visual acuity, spatial crowding, contrast sensitivity, contrast discrimination, and stereoacuity. Furthermore, their performance improvements generalized to more complex and natural tasks such as reading and aerial photography interpretation. The authors suggest that the generalized improvements are related to gains in visual processing speed.

Both the papers by Jia et al. and Liu & Zhang address the issue of monocular training and binocular visual functions in patients with amblyopia. Both studies seem

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to be consistent in their findings that monocular training has limited impact on stereo-acuity, and argue for the need for binocular or some modified monocular training. Whereas Jia et al., evaluate monocular training on a variety of binocular abilities, Liu & Zhang investigate a dichoptic technique for which participants use the amblyopic eye to practice a contrast discrimination task while the non-amblyopic eye is simultaneously exposed to a noise mask. They show that the dichoptic technique results in additional benefits for stereo acuity while visual acuity remains comparable to monocular training. Together the two papers should be very useful in informing clinicians about the design of efficient training for amblyopia patients.

3. Interactions of perceptual Learning with other cognitive and motor functions

Five of the papers in the special issue look at the relationship between perceptual learning and other cognitive and motor functions, including object category learning, the role of attention, high order cognitive processes, eye movements and their interactions with moderate exercise.

The paper by Vergeer et al. investigates learning of objects categories and neural signatures as measured by intermodulation responses (IMs) in electro-encephalography (EEG). IMs arise from non-linear interactions across stimulus frequencies leading to emergent frequency components. They find that high order IMs are present for shapes from a trained family of objects and absent for an untrained set of objects. Furthermore, the IMs are also present for new exemplars belonging to the trained family of objects but not seen previously.

Ahmadi and colleagues address the question about whether perceptual learning involves changes in the early visual cortex and/or higher cognitive processes such as attention. Using EEG and event related potential signature components, they study learning in a texture discrimination task. They find differences across various event related potentials, including early sensory and attentionally modulated components that correlated with the amount of behavioral learning as well as changes in components associated with high level cognitive processing. They conclude that perceptual learning in texture discrimination involves plasticity in early visual cortical areas, top-down attentional control, and cognitive processing.

The third paper in this group investigates the interactions between perceptual learning and physical exercise. Connell et al. examine the influences of moderate intensity exercise before or after sessions of perceptual training. They utilize a classic motion direction discrimination task. They find a trend for a detriment in learning when the subjects exercised before visual perceptual training and no influence on learning when the exercise followed the perceptual training sessions. The findings apply to the trained motion directions axis and to untrained motion directions. Together, the authors suggest that moderate exercise does not enhance perceptual learning for motion tasks nor enhance its generalization.

Previous studies have shown that a feature that is irrelevant to the training task will be learned if it is sub-threshold and outside of the focus of attention (task irrelevant perceptual learning, TIPL (Seitz & Watanabe, 2009)). TIPL does not occur when the task-irrelevant feature is suprathreshold. Galliussi and colleagues ask whether TIPL occurs when the task irrelevant feature is within the focus of attention and potentially make the feature suprathreshold. Utilizing various visual tasks on a single 3-dot stimulus presented at the fovea, they show that TIPL occurs for a Vernier acuity task even if attention is deployed to the stimulus. One interesting future step would be to quantify how varying the degree of attention modulates the TIPL learning.

Taking a step towards understanding perceptual learning in natural vision, Rolfs et al. presented stimuli during saccade preparation at a location offset from the saccade target. They observed robust perceptual learning and associated transfer costs for untrained locations and orientations. They also assessed if spatial transfer costs were reduced for the remapped location of the presaccadic stimulus—the location the stimulus would have had (but never had) after the saccade. Although the pattern of results at that location differed somewhat from that at the control location, they found no clear evidence for perceptual learning at remapped locations. Location and feature specificity subsist when the target stimulus is presented strictly during saccade preparation throughout training.

To summarize, the papers in the special issue show an exciting heterogeneity of topics covering classic questions on perceptual learning, computational modeling, EEG, reading, tactile and motor learning, the role of attention, and training methods for patients with visual deficiencies. Together they constitute a thought-provoking set of studies that will motivate future steps in the field of perceptual learning.

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