

Learning to Identify Letters:

Generalization in high-level perceptual learning

Jordan W. Suchow

Irvington High School

Mentor: Professor Denis G. Pelli

Psychology and Neural Science
New York University

ABSTRACT

Learning the perceptual task of letter identification is crucial to reading. The beneficial effects of training have been well documented for a variety of perceptual tasks. This improvement is often highly task and location specific. However, unlike the specificity of perceptual learning, many studies of conceptual learning have found a great deal of generalization between related tasks and stimuli. Three new experiments explore the specificity of letter learning. In Experiment I, observers learned to identify letters in one subset of a foreign alphabet (Chinese) before learning a second subset of that same alphabet. Observers are found to receive no benefit from having partially learned the alphabet, proving that letter learning is letter specific. In Experiment II, observers trained on the components of Chinese characters (individual brushstrokes and combinations of brushstrokes) before learning the characters themselves. The results show that observers, when learning to identify a new object, need not relearn combinations of features with which they are already familiar; in fact, knowledge of an object's parts instills a more effective learning strategy in the observer. Experiment III explores the specificity of letter learning with regard to location in central and peripheral vision. Observers' efficiency for foreign letter identification (Armenian) is found to be highly dependent on eccentricity (distance from central fixation, measured in degrees of visual angle). In sum, the results reveal two mechanisms that identify letters: a process that isolates an object's individual parts present only in central vision, and a ubiquitous process based on holistic letter shape. These two letter identification processes are likely the substrate for the letter decoding and whole-word processes that have been postulated for reading.

INTRODUCTION

We live in a visually rich world, full of readily identifiable letters, shapes, and figures that make up each scene we encounter. In order to process these complex scenes, the visual system relies on a variety of low-level visual skills, including orientation and spatial frequency discrimination, element segregation using textural cues, depth perception, and motion discrimination (Westheimer, 1996). People normally acquire the ability to make these visual judgments of the external world in infancy (Adolph & Eppler, 1998). Many eight-month-old infants are already capable of combining judgments of this sort, as seen through their ability to determine the depth of a nearby cliff from visual textural cues (Bertenthal, Campos, & Barrett, 1984). Although acquired very early in life, it is possible to improve upon these low-level judgments through training, even in adulthood. Learning through practice on such perceptual tasks tends to be quick, permanent, and highly specific to both task and stimulus, suggesting a high level of neural plasticity in early visual mechanisms (Gilbert, Sigman, & Crist, 2001).

Studies of conceptual learning have examined how observers classify arbitrary stimuli such as blobs, random dot patterns, and letter strings. When there are many features (dimensions) by which to classify an object, but few categories, observers will base their decision on a single feature, ignoring the rest (for review see Murphy, 2002). Such classifications have shown a great deal of transference to related tasks and stimuli, and consequently serve as the basis for a “knowledge model” of learning, by which observers draw from that which they already know to classify unfamiliar material (Murphy, 2002). However, identifying a letter involves many categories (the number of letters in the alphabet), which forces observers to use multiple features (Miller, 1956).

By applying the methods of conceptual categorization at a strictly visual level, it is possible to eliminate a question that has plagued researchers of conceptual learning for decades: what constitutes a feature? It has been suggested that on a conceptual level there are a

practically infinite number of possible features, including physical properties such as color, shape, and size, as well as inferred properties such as function, emotion, and origin (Murphy, 2002). However, on a visual level, features can be narrowly defined as discrete components of an image that are detected independently of each other (Pelli, Farell, & Moore, 2003).

In order for us to recognize an object, we first detect and then integrate that object's features (Watson, 1979). Even after millions of exposures, the visual system relies on this bottom-up process of independent feature detection to recognize simple shapes such as grating patches, letters, and words (Pelli et al., 2003). Doshier and Lu (1998) suggest a feature-weighting model of perceptual learning that predicts the rapidly diminishing improvement found in many perceptual learning studies and emphasizes feature recognition as the basis for learning to identify objects. However, very little is known about how we integrate features when identifying objects, and even less is known about how we learn to do so.

Presumably, images that appear to be identical share a large number of features. Letters provide a valuable tool for studying object identification in that they are diverse, and of obvious practical use. Many letters within an alphabet share identical structural elements, and presumably share features.



Figure 1. (a) The letters b, d, p, and q are identically shaped figures flipped horizontally and vertically. (b) The letters E, F, H, I, L, and T consist of vertical and horizontal bars.

Some writing systems provide a more rigid structure for shared features. Chinese is unique in that it embodies a hierarchy of common written forms, and by extension, features. On the most basic level is the *brushstroke*, a straight or curved line of specific orientation. *Radicals*, specific combinations of brushstrokes, can stand alone as *characters*, but are often combined with other radicals to form more complex characters. While each character

represents a word, multiple characters can be combined to create new, more complex, words (McNaughton & Ying, 1999).

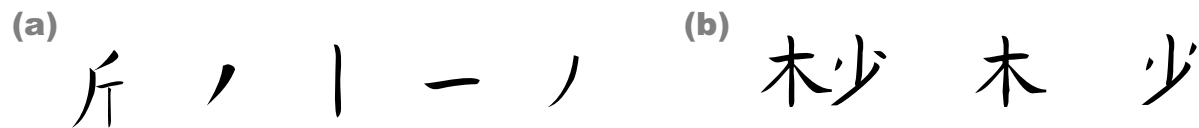


Figure 2. (a) The Chinese radical JIN is comprised of four brushstrokes. (b) The Chinese character MIAO is comprised of two radicals, MU and SHAO. These brushstrokes and radicals appear in hundreds of other characters, and, together with a limited number of other brushstrokes and radicals, form the entire vocabulary of written Chinese.

In Experiment I, observers train on a subset of five common Chinese characters through a letter identification task before learning a second subset of five common Chinese characters. If observers can both infer a letter's parts and use those parts to identify new letters, then observers should perform more efficiently on their second set than on their first, as they would have fewer new features to learn. Chinese characters, since they share brushstrokes, should exhibit some level of generalization.

In Experiment II, observers train on either the component brushstrokes or radicals of a subset of Chinese characters before learning the subset itself. This assesses the extent to which observers can use familiar elements in identifying an unfamiliar object. The classical model of learning holds that prior knowledge is most beneficial to the acquisition of new knowledge when the prior knowledge closely resembles that which is to be learned (Posner & Keele, 1968). This model predicts that radical training will impart a greater advantage than brushstroke training, as radicals more closely resemble the characters to be learned.

Much rests on the notion that knowledge of a character's parts benefits the learning of new characters containing those parts. A popular tool for learning Chinese, *Reading & Writing Chinese*, bases its methodology for introducing new characters on this very concept (McNaughton & Ying, 1999). As the preface says, "A popular feature of the first edition has been retained, namely, the introduction of new characters only in combination with

characters already learned, so as to lessen the burden of learning the new combination and to provide a review of the characters already learned.”

In Experiment III, observers train on subsets of the Armenian alphabet displayed at an *eccentricity* (distance from a central fixation point) of 0, 5, or 15 degrees before being tested on those same subsets at eccentricities of 0, 5, and 15 degrees. Peripheral presentation of stimuli provides a useful tool: by placing a letter at more than the *critical eccentricity* (equal to roughly twice the square root of the image area), the letter can no longer be recognized by its parts. This is because those parts lie within a single isolation field and crowd one another, causing the letter to seem scrambled (Bouma, 1970). Instead, the observer must holistically recognize the entire letter as a single part, relying on overall shape to identify the letter (Martelli et al., 2004).



Figure 3. Fixate the point to the left of the letter at which you can just barely identify it. We found threshold at \pm . Identification fails at $-$ but succeeds at $+$. When fixating the $+$, both letter shape and feature content are available. When fixating the $-$, however, only letter shape is available.

By testing observers on letters displayed at both trained and untrained eccentricities, the observers’ ability to generalize between by-parts and holistic recognition is assessed. Central learning (0 degrees eccentricity), being based both on holistic letter shape and by-parts feature content, should not fully generalize to the periphery, in which only a letter’s shape is available. Conversely, peripheral learning, being based solely on letter shape, should fully generalize to central vision, where letter shape is also available.

In short, a series of three experiments explores the specificity of letter learning over a broad spectrum, ranging from a character’s individual parts to sets of letters. Exploring this specificity on multiple levels illuminates the interaction between objects and their parts during letter identification.

GENERAL METHODS

Observers performed an identification task, in which they were asked to identify a briefly presented signal (200 ms) in visual noise.

Stimuli

All stimuli were rendered on an Apple Power Macintosh running MATLAB (Mathworks) in conjunction with the Psychophysics Toolbox extension (Brainard, 1997; Pelli, 1997). Signals were displayed on a cathode ray tube (CRT) monitor with a background luminance of 24 cd/m^2 . CRT monitors use an electron gun to produce a controlled luminance at the screen. For this investigation, we used only the green gun; this allowed for the fine adjustments to contrast needed in order to render near-threshold signals (Pelli & Zhang, 1991). The display resolution was set to 1024×768 at 75 Hz, 29 pixel/cm. All runs were conducted from a viewing distance of 50 cm.

Observers

All observers had normal or corrected-to-normal acuity and normal contrast sensitivity, and had no previous exposure to the characters on which they were training. All observers were over the age of 10, the age at which efficiency for letter identification becomes independent of age (Mishra et al., 2002). Four observers (DBN, ELS, JWS, & SAS) participated in Experiment I. Three observers (ARM, GRL, & SMT) participated in Experiment II. Two observers (JWS & SAS) participated in Experiment III. JWS is the author.

Procedure

The observer was asked to fixate a central black square subtending 0.15 degrees on the monitor. After the observer initiated the run by clicking a mouse, the signal appeared for 200 ms, replacing the fixation point. The signal was then replaced by a high-contrast response screen containing all of the possible signals. The observer used a mouse-controlled cursor to select the character from the response screen that matched the signal. Correct responses were

awarded a short beep, and any response automatically initiated the next trial, consisting of another stimulus presentation and observer response. Observers performed runs of 40 consecutive trials.

Experiments II and III utilized a slightly altered procedure to that detailed above, as the response screen was rendered at a contrast of zero, thus appearing blank and ensuring that the observer only viewed the characters during stimulus presentation. The observer was initially instructed to match each of the still unfamiliar signals with an unknown but fixed corner of the screen. Consequently, the observer was at first forced to utilize trial and error guessing in order to discover which signal was associated with each corner of the screen. When a blank response screen was utilized during central learning, all observers overcame this additional requirement of the task within the first 40 trials. Accordingly, the figures do not plot the observers' initial run for each new subset learned using a blank response screen.

In order to determine an observer's efficiency for the identification task, the QUEST sequential estimation procedure was used (Watson & Pelli, 1983). The QUEST procedure extrapolates from already-known information regarding both the task and observer, as well as from the observer's performance throughout the task, to calculate an *identification contrast threshold*, defined as the signal contrast (ratio of luminance increment to background luminance) at which the observer can correctly identify the signal 64% of the time. The threshold of a house is the plank dividing inside from out. The visual threshold of the observer is the contrast that divides the seen from the unseen. After each trial, the QUEST procedure calculates a threshold estimate, which determines the contrast at which the next stimulus will be presented. By placing each trial at the current threshold estimate, the uncertainty of the final threshold estimate is minimized. In effect, if the observer correctly identifies the signal, the next trial is rendered at a lower contrast. If he incorrectly identifies the signal, the next trial is rendered at a higher contrast.

Regardless of the signal contrast, noise is added independently to each pixel of the stimulus, such that the luminance of any particular pixel is the sum of the luminance assigned to that pixel by the signal's contrast and a random increment or decrement in luminance sampled from a zero-mean Gaussian distribution, truncated at ± 2 SDs.



Figure 4. English letters of decreasing contrast (left to right) with added “white” noise, containing equal energy at all frequencies. Visual noise interferes with our ability to recognize objects (Pelli & Farrell, 1999). How far can you read? The average among our observers is 7 letters.

Although contrast thresholds are useful, comparisons of *efficiency* allow for a greater range of flexibility because they are independent of the task, and thus provide a pure measure of human performance (Pelli & Farrell, 1999). Efficiency is defined as the ratio of the energy (product of squared contrast and “ink area”) needed by the Ideal Observer (a template matching algorithm) to the added energy needed by the human observer in the presence of added noise:

$$\eta^+ = \frac{E_{\text{ideal}}}{E - E_0} \quad (1)$$

where E_{ideal} is the energy used by the Ideal Observer, E is the energy threshold, and E_0 is the energy threshold measured without noise. The Ideal Observer uses the least possible amount of energy needed to perform the task, such that efficiency is always less than or equal to 1 (Pelli et al., 2005). Amazingly, the Ideal Observer can correctly identify all ten letters presented in Figure 4. The letter of lowest contrast, a “C”, falls at the Ideal Observer’s 64% correct threshold.

EXPERIMENT I: TRANSFERENCE BETWEEN COMMON WORDS

EXP. I. METHODS

Stimuli

The stimuli were character-shaped luminance increments of ten common Chinese characters (Table 1), originally used by Pelli et al. (2005) for their study of letter identification. They are based on high-resolution scans of Yung Chih-sheng's calligraphy. Stimuli were randomly distributed into two subsets of five characters.

Table 1: Subsets of Chinese characters

Subset	Characters
Yung 1	會 說 是 問 兩
Yung 2	多 請 少 好 見

Task

Observers trained on a single subset by performing 25 consecutive runs of the letter identification task (with a high contrast response screen) before training on a second subset in the same manner.

EXP. I. RESULTS

Observers were no better at identifying an unfamiliar subset of Chinese characters after having already learned five characters of the same alphabet (Figure 5). Nonetheless, observers did recognize that both subsets came from the same alphabet, noting that they “look similar.”

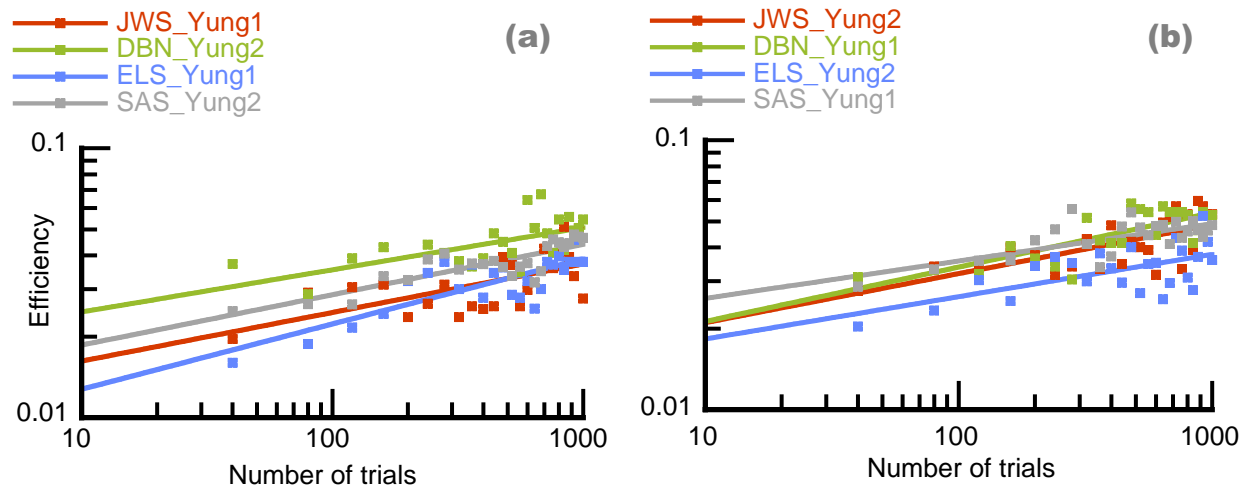


Figure 5. Learning curves for observers training on multiple 5-character subsets of Chinese. (a) Learning curves for observers training on their first subset. (b) Learning curves for observers training on their second subset. Each point represents a single 40-trial threshold estimate. Note the similarity of learning curves between observers, as well as between each observer's first and second subset. Using the same stimuli, Pelli et al. (2005) found efficiency for fluent observers (those who had both primary schooling in the alphabet and were fluent readers of literature in the alphabet) to be 5.1 percent. Here, observers reach 5.1 percent efficiency after approximately 1,000 trials (200 trials/letter).

EXPERIMENT II: TRANSFERENCE BETWEEN PARTS AND WHOLE

EXP. II. METHODS

Stimuli

Stimuli were brushstroke, radical, and character-shaped luminance increments of Chinese. Four characters comprised of two four-brushstroke radicals were used (Table 2). All stimuli were created in Adobe Fontographer by reconfiguring the font used in Experiment I.

Table 2: Characters and their component brushstrokes and radicals

Character	Pinyin name	English meaning	Component radicals		Component brushstrokes	
杪	MIAO	beard of grain; smallest part; a measure for seconds	木	少	丨	一
牧	MU	to herd or tend	牛	攴	㇏	㇏
环	HUAN	to encircle; ring or bracelet	王	丩	ノ	㇏
欣	XIN	to be happy	斤	欠	㇏	ノ

Procedure

Observers completed two stages in succession: *training* and *learning*. During training, observers performed 25 runs of the identification task on either the eight component radicals of the character set, or the ten component brushstrokes of the character set. Observer GRL received no training. During learning, observers performed 25 runs of the identification task on a set of four characters (Table 2).

EXP. II. RESULTS

Radical and brushstroke training were found to improve efficiency for identifying a set of characters comprised of those radicals and brushstrokes. Additionally, the presented learning curves (linear regression on log-log axis) do not predict a convergence of efficiency, as would be expected if brushstroke or radical training simply provided an advantage equivalent to a certain number of trials. Instead, extrapolation of the learning curves predict that training on an object's parts instills a more effective learning strategy, such that an observer without the training would never make up the deficit.

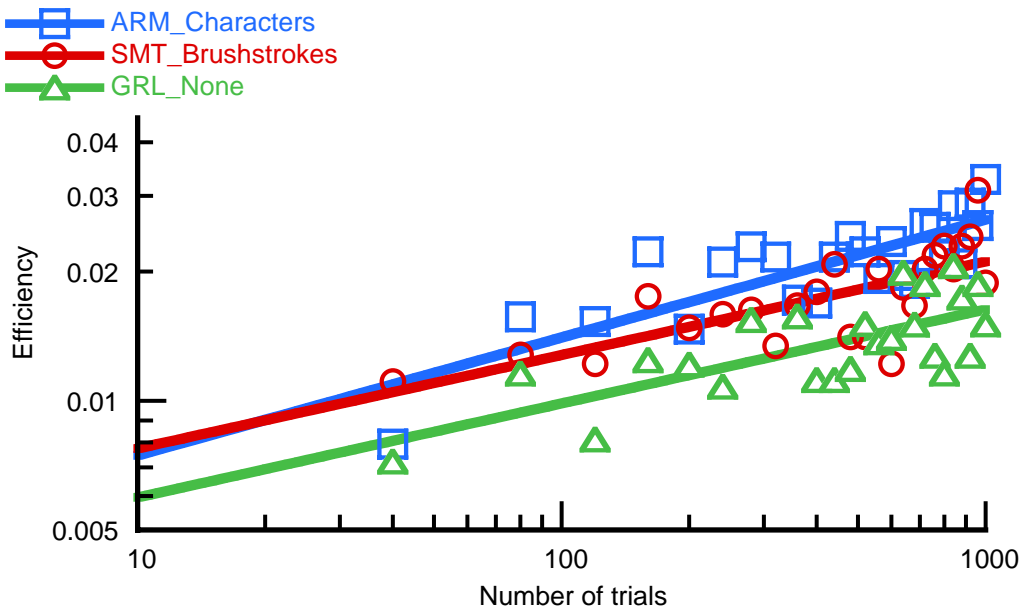


Figure 6. Efficiency as a function of number of trials for observers with radical, brushstroke, or no training. Brushstroke training improves efficiency after 1,000 trials by 25%. Radical training improves efficiency after 1,000 trials by 50%. Note that the learning curves do not predict a convergence of efficiency.

EXPERIMENT III: PERIPHERAL LEARNING

EXP. III. METHODS

Stimuli

Stimuli were letter-shaped luminance increments of the Armenian alphabet. Letters were randomly distributed into three subsets of four characters.

Table 3: Subsets of the Armenian alphabet.

Subset	Characters
Nork A	Ի Զ Տ Լ
Nork B	Ր Ն Բ Պ
Nork C	Ս Ժ Թ Մ

Task

Observers performed the letter identification task on stimuli placed 0, 5, or 15 degrees in the periphery. After the observers had learned a given set, they were tested on that same set at an eccentricity of 0, 5, and 15 degrees.

EXP. III. RESULTS

Figure 7 shows observers' learning curves for letters learned at 0, 5, and 15 degrees in the periphery. Observers show a strong eccentricity-dependence that weakens over time.

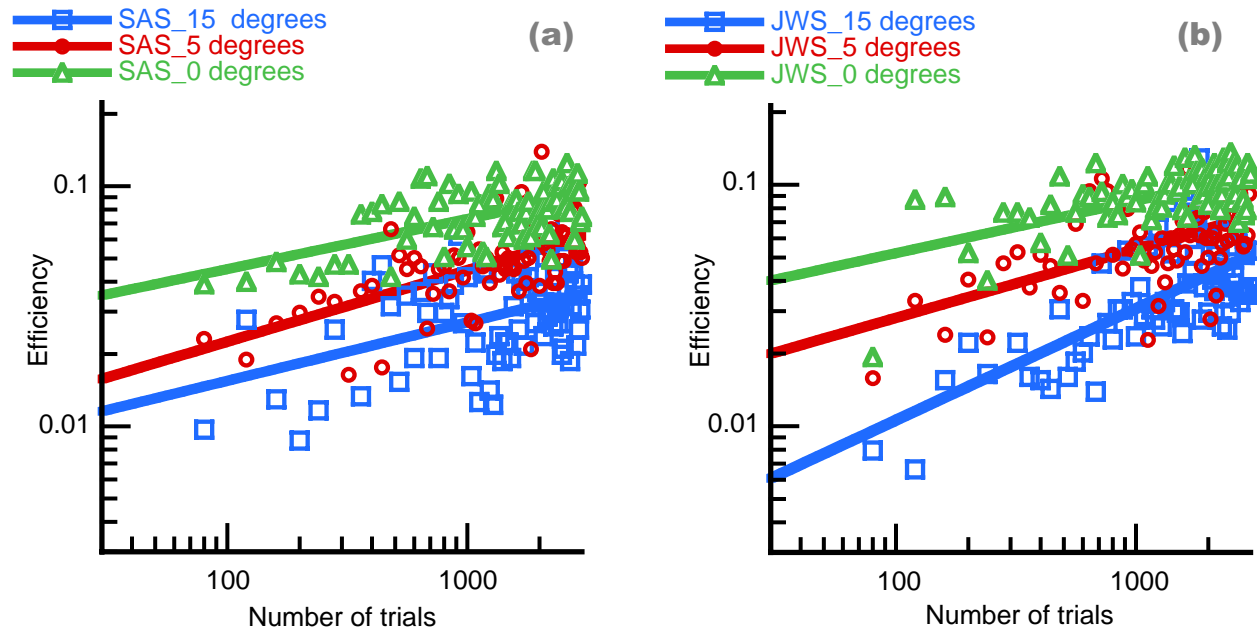


Figure 7. Learning curves for identification of Armenian letters displayed at 0, 5, and 15 degrees from fixation. Using the same stimuli, Pelli et al. (2005) found central efficiency for fluent observers to be 9.4 percent. Here, observers reach 9.4 percent efficiency after approximately 1,000 trials (200 trials/letter). (a) Observer SAS. (b) Observer JWS.

Figure 8 shows efficiency at both trained and untrained eccentricities. Observers perform best when they have trained at the same eccentricity at which they are being tested, however, central learning is far more location-specific.

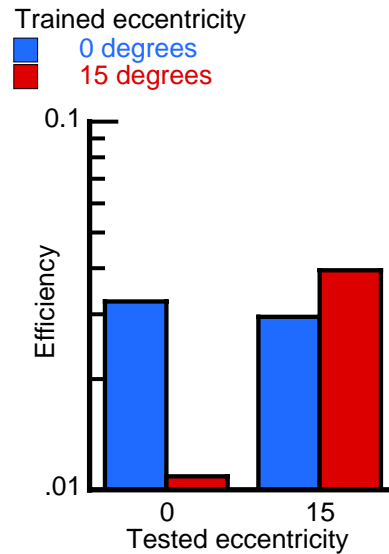


Figure 8. Efficiency for letter identification at trained and untrained eccentricities. Each bar represents a single 40-trial threshold estimate, averaged across the two observers. Training at 0 degrees was only beneficial when tested at 0 degrees. Training at 15 degrees was equally beneficial when tested at 0 or 15 degrees. This shows that what is learned at 0 degrees is specific to central vision, whereas what is learned at 15 degrees generalizes to all eccentricities.

GENERAL DISCUSSION

Remarkably, an exposure of only 50 seconds per letter at near-threshold contrast is enough to triple an observer's efficiency for identifying a previously unfamiliar set of characters. The observer's improved efficiency can only have come from the experience of categorizing the near-threshold signals. Additionally, an observer's efficiency remains unaffected by exposure to a high-contrast response screen, which validates the use of such a screen when measuring efficiency. Along these lines, it would be interesting to determine whether correct-response feedback is functionally useful to observers.

Surprisingly, letter learning is found to be letter-specific even amongst letters that share common structural elements. Observers may lack the ability to infer an object's parts from their knowledge of the entire object. Similarly, it is possible that the parts they do derive are not the same parts upon which the language is structurally built. For instance, observers may consider the junction of two lines or empty spaces caused by surrounding curvatures to be

significant structural elements, while far fewer of these would appear in other characters. This also reveals why radical training is more advantageous than brushstroke training: radicals contain not only a character's structural elements, but also include information about how they are related spatially, which may in turn affect the number of features in the character. Letters are not simply the sum of their parts.

Pelli et al. (2005) found efficiency for fluent observers to be independent of eccentricity out to 5 degrees. Here, observers initially exhibit strong eccentricity dependence, but the learning curves predict a convergence of 0-degree and 5-degree peripheral efficiency after 10,000 trials. Finding that training lessens eccentricity dependence is evidence for a holistic learning process by which observers improve upon their ability to recognize an object without isolating its parts.

Learning in the periphery (15 degrees eccentricity) generalizes well to central vision (0 degrees), but central learning does not generalize to the periphery. This is likely because only central viewing allows observers to isolate a letters parts. When displayed peripherally, the letter must be recognized holistically, as the isolation field necessary to isolate the letter's parts covers an area roughly $\times 14$ greater than the letter itself (Pelli et al., 2004). This is consistent with the finding that observers who have reached a central efficiency of 10 percent revert to the efficiency of holistic learning when those same stimuli are presented peripherally.

These results show that letter identification is mediated by two processes that improve with practice: a dominant by-parts process in central vision and a weaker holistic process that operates both in central and peripheral vision. Similarly, studies of reading have found two processes that contribute to reading rate, recognizing words by content (letters) or shape (Stanovich, 2000; Su et al., 2004). Recognizing words by content is like by-parts letter recognition, and recognizing words by shape is like holistic letter recognition. Thus, this study goes beyond existing conjectures about reading words to reveal the roles of by-parts and holistic object recognition in letter identification.

CONCLUSION

Three experiments are presented, applying the methods of conceptual learning to perceptual letter learning. Letter learning is found to be quick, letter-specific, and eccentricity dependent. Observers triple their efficiency for identifying a previously unfamiliar alphabet from a total of only 50 seconds per letter of near-threshold exposure. Observers, when learning to identify a letter, need not relearn combinations of features with which they are already familiar. In fact, knowledge of an object's parts instills a more effective learning strategy in the observer. Central learning is location-specific, while peripheral learning generalizes well to other locations. These results strongly suggest a dual mechanism approach to learning letters: a central by-parts process by which observers associate parts of letters with which they are already familiar, and a ubiquitous holistic process that relies on letter shape.

ACKNOWLEDGMENTS

The deepest of thanks to Professor Denis Pelli, to whom I am indebted for all that he has provided for me over the past two years, including his excellent advice and guidance, his thoughtful critique of my arguments and design, and his ability to ask just the right question. Thank you to Dr. Najib Majaj, Dr. Ragnar Steingrímsson, Dr. Marialuisa Martelli, Allen Ingling, Michael Su, Tracey Berger, Katharine Tillman, Betty Kolod, Lyuba Azbel, Henny Admoni, and all who have been a part of the Pelli lab during my time there, for they all have created an exciting atmosphere of logical debate and analysis that has made Wednesday my favorite day of the week. A sincere thank you to Mr. Robert Sim, who graciously allowed for my use of both his room and computer at Irvington High School. Thank you to all of my friends and family, who have supported me by freely providing their time, energy, and open ears. Last, but certainly not least, I am immeasurably appreciative of my parents, Eva and Steven Suchow, for all that they have done for me, and whose sincere interest in my work has been of extraordinary value.

REFERENCES

- Adolph, K.E. & Eppler, M.A. (1998) Development of visually guided locomotion. *Ecological Psychology*, 10 (3-4) 303-321.
- Bertenthal, B.I., Campos, J.J., & Barrett, K.C. (1984) Self-produced locomotion: An organizer of emotional, cognitive, and social development in infancy. In R.N. Emde & R.J. Harmon (Eds.), *Continuities and discontinuities in development*. (pp. 175-210). New York: Plenum.
- Brainard, D.H. (1997) The Psychophysics Toolbox. *Spatial Vision*, 10 (4), 433-436.
- Dosher, B.A. & Lu, Z.-L (1998) Perceptual learning reflects external noise filtering and internal noise reduction through channel reweighting. *Proceedings of the National Academy of Sciences of the United States of America*, 95, 13988-13993.
- Farah, M.J., Wilson, K.D., Drain, M., Tanaka, J.N. (1998) What is “special” about face perception? *Psychology Review*, 105(3), 482-498.
- Gilbert, C.D. (1994) Early perceptual learning. *Proceedings of the National Academy of Sciences of the United States of America*, 91, 1195-1197.
- Gilbert, C.D., Sigman, M., & Crist, R.E. (2001) The neural basis of perceptual learning. *Neuron*, 31, 681-697.
- Martelli, M., Majaj, N.J., & Pelli, D.G. (2004) Are faces processed like words? A diagnostic test for recognition by parts. *Journal of Vision*. In press.
- McNaughton, W. & Ying, L. (1999) *Reading & writing Chinese*. Boston: Turtle Publishing.
- Miller, G.A. (1956) The magic number seven, plus or minus two: some limits on our capacity for processing information. *Psychological Review*, 63, 81-97.
- Mishra, A., Baweja, G., Martelli, M., Chen, I., Fox, J., Majaj, N.J., & Pelli, D.G. (2002) How efficiency for identifying objects improves with age. European Conference on Visual Perception, Glasgow, August 2002.
- Murphy, G.L. (2002) *The big book of concepts*. Cambridge: The MIT Press.

- Pelli, D.G. (1997) The VideoToolbox software for visual psychophysics: transforming numbers into movies. *Spatial Vision*, 10, 437-442.
- Pelli, D.G., Burns, C.W. Farrell, B, & Moore, D.C. (2005) Identifying letters. *Vision Research*. In press.
- Pelli, D.G. & Farrell, B. (1999) Why use noise? *Journal of the Optical Society of America A*, 16, 647-653.
- Pelli, D.G., Farrell, B., & Moore, D. C. (2003) The remarkable inefficiency of word recognition. *Nature*, 423, 752-756.
- Pelli, D.G., Martelli, M.L., & Majaj, N.J. (2004) Using crowding to determine whether an object is identified as a whole or by parts. *Vision Sciences Society*, Sarasota, Florida, April 30-May 5, 2004.
- Pelli, D.G., & Zhang, L. (1991) Accurate control of contrast on microcomputer displays. *Vision Research*, 31, 1337-1350.
- Posner, M.I., & Keele, S.W. (1970) On the genesis of abstract ideas. *Journal of Experimental Psychology*, 77, 353-363.
- Stanovich, K.E. (2000). *Progress in understanding reading: scientific foundations and new frontiers*. New York: Guilford Press.
- Su, M., Berger, T.D., Majaj, N.J., & Pelli, D.G. (submitted). Crowding, shuffling, and capitalizing reveal three processes in reading. *Journal of Vision*.
- Watson, A.B. (1979) Probability summation over time. *Vision Research*, 19, 515-522.
- Watson, A.B., Pelli, D.G. (1983) QUEST: A Bayesian adaptive psychometric method. *Perception and Psychophysics*, 33, 113-120.
- Westheimer, G. (1996) Location and line orientation as distinguishable primitives in spatial vision. *Proceedings of the Royal Society of London B*, 263, 503-508.