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An LDA Approach to the Neural Correlates of Configural Learning

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Abstract

The purpose of our current study is to employ linear discriminant analysis (LDA; Philiastides & Sajda, 2006) to characterize the changes in ERPs over the entire course of a perceptual learning task. Configural learning is the perceptual learning process by which participants develop configural processing strategies or representations characterized by extremely efficient parallel information processing (Blaha & Townsend, Under Revision). Participants performed a perceptual unitization task in which they learned to categorize novel images. Correct categorization responses required exhaustive feature identification, which encouraged unitization of images into unified object percepts. Linear discriminator accuracy, measured by A_z, increased each day of training, showing significant differences in neural signals between categories on and after training day 3 or 4 for all participants. Additionally, the LDA training window starting time resulting in discriminator performance of 65% accuracy or better shifted from 450–500ms to 300ms after stimulus onset at the completion of training. LDA results are consistent with our earlier report (Blaha & Busey, 2007) of peak ERP amplitude differences between categories after training at approximately 170ms and 250ms after stimulus onset. Our EEG results are consistent with the hypothesis that perceptual unitization results in configural perceptual processing mechanisms.

Keywords: Linear Discriminant Analysis; Evoked Response Potential; Configural Processing; Perceptual Learning; Capacity

Introduction

Configural learning is the process by which configural information processing mechanisms develop over the course of extensive perceptual training. From the perspective of information processing, if an object is treated configurally, or as a Gestalt, all the features are processed simultaneously and statistically facilitate each others' processing rates. Through this facilitation, the decisions made about all features are faster than features made on any subset of features, indicating a highly efficient use of information. In the formal terminology of human information processing models, we define configural mechanisms as a facilitatory parallel system exhibiting super capacity efficiency under an exhaustive stopping rule (Wenger & Townsend, 2001). This system provides a well-defined model by which to examine mechanisms thought to underlie both face processing and visual expertise.

Blaha and Townsend (Under Revision) proposed that the result of configural learning is this facilitatory, parallel configural processing model. To characterize the configural learning process, Blaha and Townsend applied the Capacity Coefficient measure of work-load efficiency Townsend and Wenger (2004) to data from a perceptual unitization learning task. Unitization is the perceptual learning mechanism whereby people group or "chunk together" smaller object features into fewer, larger perceptual features over training (Goldstone, 1998, 2000). With the boundary conditions for the occurrence of unitization already well established (Goldstone, 2000), Blaha and Townsend (Under Revision) showed that unitization is characterized by a shift from extreme limited to extreme super capacity processing. The super capacity at the end of training was predicted by Hebbian-style feedback learning resulting in facilitatory parallel processing. Hence, unitization results in the development of configural processing mechanisms for initially novel visual objects.

With our behavioral findings that configural learning results in configural information processing mechanisms, we would like to find converging evidence of neural configural processing mechanisms developing during configural learning. Evidence from studies of both real-life and laboratory-trained experts demonstrated N170 peak amplitude differences for the visual response to objects of expertise. Often these ERPs are similar to the responses to faces. Researchers proposed that the neurological response of visual expertise engages configural processing strategies to which the N170 is sensitive (Busey & Vanderkolk, 2005). The N250 ERP component has also demonstrated sensitivity to expertise training and is sometimes referred to as a marker of visual expertise (Scott, Tanaka, Sheinberg, & Curran, 2006). Few studies, however, have closely examined the development of these neural correlates of configural or expert processing.

We propose that the observed changes in information processing over the course of configural learning should be accompanied by changes in neurological measures of perception; in particular, we expect the N170 and N250 peak amplitudes to change as configural object representations are developed in our unitization learning task. Indeed, our preliminary ERP analyses exhibited post-training differences in both the N170 and N250 peak amplitudes for objects processed with configural mechanisms compared to non-configurally processed objects (Blaha & Busey, 2007).

However, peak ERP amplitude analyses limit our understanding of the configural learning process, because a large amount of information about both the distribution of EEG responses within a single training session and the changes in these distributions across the days of training is lost through the averaging of signals. Our behavioral model of learning, namely the Capacity Coefficient, provides a fine-grained index over the response time (RT) distribution for each day of configural learning. This enables an examination of processing efficiency both within a single training session and across the entire configural learning task. An analogous measure of the EEG signal is needed to more thoroughly investigate the changes in the scalp potentials over the entire course of configural learning.

Sajda and colleagues (Parra, Spence, Gerson, & Sajda, 2005; Philiastides & Sajda, 2006) proposed an LDA approach to EEG analysis that provides a means of investigating the neural correlates of two-choice discrimination tasks. In a study of face/car classification Philiastides and Sajda (2006) identified two training windows for the linear discriminator resulting in high classification performance. These windows, centered around 170ms and 300ms after stimulus onset, indicated two time points in the EEG signal that strongly differentiated the input image information, providing a sort of neural discrimination time for each trial.

Our configural learning task is a categorization task in which participants must learn to categorize a fixed set of novel visual objects. The individual object features are grouped together so that correct Category 1 responses require exhaustive processing of all features; configural learning mechanisms develop for the objects belonging to this conjunctive category. We apply the LDA tools of Sajda and colleagues on each day of training to locate the time windows and electrode locations in which the EEG signal differentiates the categories. As learning proceeds, we predict that the training windows differentiating the categories will shift earlier in time, indicating faster and perhaps more efficient neural responses concurrent with the emergence of the facilitatory, parallel, super capacity configural processing mechanisms.

Method

Participants

Four members of the Indiana University, Bloomington, community (2 male, 2 female), ages 20 to 24, volunteered for this study. All were right-handed with normal or corrected-to-normal vision. Participants were monetarily compensated for their participation.

Apparatus

EEG was sampled at 32 channels at 1000Hz and downsampled to 500Hz. It was amplified by a factor of 20,000 (Sensorium amps) and band-stop filtered at 58-62Hz. Signal recording sites included a nose reference and a forehead ground. All channels had below 5kΩ impedance, and recording was done inside a Faraday cage. Data were analyzed using the EEGLab toolbox (Delorme & Makeig, 2004).

Images were shown on a 21in (53.34cm) Mitsubishi color monitor model THZ8155KL running at 120Hz. Images were approximately 44in (112cm) from the participant. Responses were collected with two buttons on an 8-button button box.

Stimuli

Novel visual objects were created by connecting five 'squiggle' line segments into a single 'squiggly' line. The five segments were chosen randomly from sixteen possible segments. Each segment measured 1cm in length, so the entire line measured 5cm in length. The ends of this line segment were connected by a semicircle to create a closed object. Sample stimuli are pictured in Figure 1, with letters assigned here to each segment for ease of reader identification.

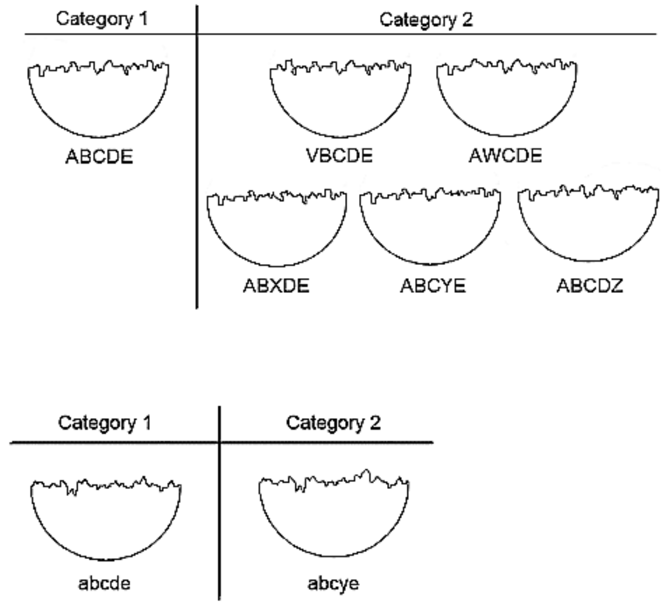

Figure 1: Example stimuli for both the conjunctive task (top) and single-feature task (bottom). Each Category 2 object contains a single segment different from the segments defining Category 1. Letters, not part of the training stimuli, are provided here to aid identification of individual squiggle segments.

Categorization Tasks

Two different category structures were used for the categorization tasks. Different sets of segments were used in the two tasks, so that the two tasks had no features, or entire objects, in common. For the conjunctive task, Category 1 contained a single object, that is, a single set of five connected features (see Figure 1, upper panel, left-hand side). Five objects belonged to Category 2, with each object having a single, unique variation of the set of features contained in the Category 1 object. That is, each Category 2 object had four features identical to those in Category 1 and one feature that differed from the Category 1 object. Each variation in Category 2 was made with a new feature. Thus, Category 2 introduced five new features, with each new feature in a different position along the squiggly line segment. Consequently, no single feature was diagnostic for the entire categorization task. Hence, a correct decision on Category 1 was a conjunctive categorization decision requiring the participant to exhaustively examine all features prior to making a response.

The single-feature task only required the participant to find and identify a single diagnostic feature for correct categorization. Depicted in Figure 1 (lower panel), the categories for the single-feature task each contained a single five-feature item, completely different from any of the objects in the conjunctive task. Here, however, the Category 2 object contained a single feature different from the Category 1 object, and the remaining four features were identical. For example, if we labeled the five features in the Category 1 object ABCDE and the single object in Category 2 contained features ABXYE, then a correct decision could be made by simply identifying the fourth feature.

Procedure

Participants completed 14 experimental sessions, including 7 training sessions of the conjunctive categorization task and 7 training sessions of the single-feature categorization task. Each session consisted of 1200 trials broken into 8 blocks of 150 trials, lasting approximately one hour. Participants could take breaks between any experimental blocks, with a mandatory break after completing 4 blocks. Over the 14 training sessions, participants alternated between the conjunctive and single-feature tasks. Note that for the single-feature task, participants were randomly assigned to a critical feature condition. EEG recordings were done on every day of conjunctive categorization training and on only the first and last days of single-feature categorization training. The remaining training days of the single-feature task were only behavioral training sessions.

EEG was recorded from 100ms prior to stimulus onset to 700ms after stimulus onset. Stimuli were centrally presented for 250ms and were replaced by a blank screen until the earlier of a button-press response or 5000ms. Auditory tone corrective feedback was given on each trial.

For both categorization tasks, participants were instructed to simply decide the category membership of each object and to use the auditory feedback to guide their decisions. They were not told how to determine category membership, nor were they informed of the number of diagnostic features for any task.

Capacity Analyses

Workload capacity was measured with the Capacity Coefficient (Townsend & Wenger, 2004), which is defined by:

$$C(t) \quad = \quad \frac{\Sigma_{i=1}^{n} K_i^1(t)}{K^n(t)}$$

where for $j = 1, \ldots, n$ simultaneously operating processing channels $K^j(t) = \int_0^t \frac{f^j(\tau)}{F^j(\tau)} d\tau = \log\left(F^j(t)\right)$ is the conditional probability that processing finished at time t given that it finished at or before time t. $F(t) = P(T \leq t)$ is the empirical RT cumulative distribution function (CDF). $K(t)$ is analogous to an integrated hazard function and can be interpreted as the amount of work completed in t amount of time. Note that in this study, $n = 5$, allowing one channel for each of the 5 features in the novel objects.

The capacity coefficient is the ratio of the amount of work completed in t time during the conjunctive processing of all features to the summed amount of work completed in the same time t completed on the processing of each feature individually. We estimate the numerator from the empirical RT CDF from the single-feature task. The denominator is estimated from the empirical RT CDF from the conjunctive task.

$C(t) = 1$ is predicted by an unlimited capacity independent parallel (UCIP) model, often referred to as standard parallel processing. $C(t) < 1$ indicates limited capacity processing, wherein processing of features slowed as more features needed to be processed simultaneously. $C(t) > 1$ indicates super capacity processing, meaning that additional features facilitated faster processing of all features.

LDA

Following Philiastides and Sajda (2006) and Parra et al. (2005), we trained a linear discriminator by using logistic regression to identify optimal bases for discrimination between categories. A series of training windows were defined for a duration of 10ms starting every 20ms over the 800ms epoch of EEG recording. A maximally discriminating spatial weighting vector $\mathbf{w}_\tau$ was estimated for each training window and used to define 'discriminating components' $\mathbf{y} = \mathbf{w}_\tau^T \mathbf{X}$ where $\mathbf{X}$ is the **N***x***T** data matrix (**N** sensors, **T** time points).

We can visualize the locus of the discriminating components withe the coupling coefficients $\mathbf{a} = \frac{\mathbf{Xy}}{\mathbf{y}^T\mathbf{y}}$. Coupling coefficients are the projection of the discriminating components onto the scalp, illustrating the correlation of each electrode with $\mathbf{y}$. That is, the coupling coefficients tell us the strength of each electrode's contribution to the discriminating components.

Linear discriminator performance was measured with A_z, the nonparametric area under the receiver operating characteristic curve. Note that LDA was applied to the conjunctive task only.

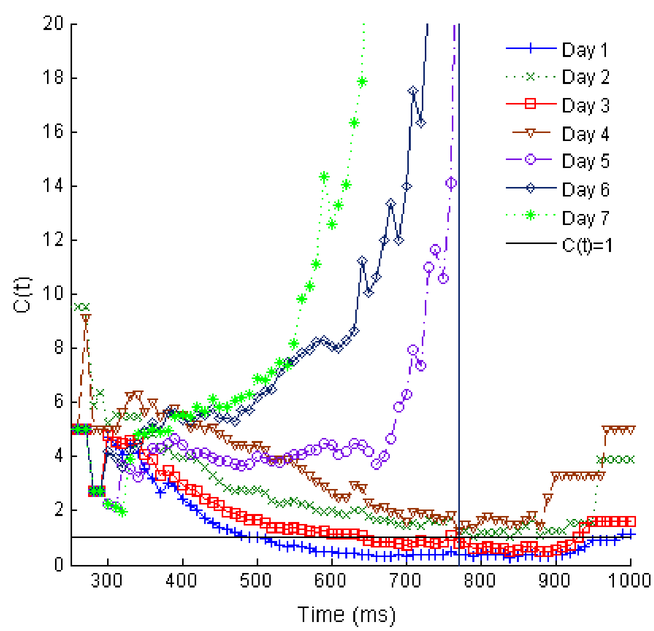

Figure 2: C(t) results over all training days for Participant BS.

Table 1: Individual Participant Results.

	Training Day	Conjunctive Mean RT	$C(t)$	Peak A_z	Peak A_z LDA Training Window	65% LDA Training Window
AB	1	366.68ms	Super	0.6149	60ms	N/A
	2	533.00ms	Super	0.6356	500ms	N/A
	3	818.92ms	Limited	0.7004	540ms	440ms
	4	737.99ms	Unlimited	0.7815	440ms	340ms
	5	697.13ms	Limited	0.7878	440ms	320ms
	6	554.87ms	Super	0.7621	440ms	240ms
	7	481.85ms	Super	0.7712	340ms	300ms
BS	1	681.22ms	Limited	0.6140	620ms	N/A
	2	544.64ms	Super	0.6416	680ms	N/A
	3	595.10ms	Unlimited	0.6360	540ms	N/A
	4	510.95ms	Super	0.7271	640ms	440ms
	5	505.68ms	Super	0.7207	540ms	360ms
	6	477.68ms	Super	0.7620	560ms	300ms
	7	472.74ms	Super	0.7222	460ms	360ms
DW	1	523.75ms	Limited	0.6243	680ms	N/A
	2	537.13ms	Limited	0.6331	520ms	N/A
	3	547.32ms	Limited	0.6720	540ms	520ms
	4	514.31ms	Unlimited	0.7043	500ms	400ms
	5	483.38ms	Unlimited	0.7043	520ms	260ms
	6	430.03ms	Super	0.7408	420ms	260ms
	7	401.37ms	Super	0.7289	420ms	280ms
PG	1	704.58ms	Limited	0.6284	540ms	N/A
	2	645.69ms	Limited	0.6658	560ms	540ms
	3	536.18ms	Unlimited	0.6980	520ms	460ms
	4	492.58ms	Super	0.6735	580ms	460ms
	5	502.10ms	Super	0.7048	540ms	460ms
	6	499.91ms	Super	0.7006	480ms	440ms
	7	450.60ms	Super	0.736	520ms	380ms

Results

Individual participants' $C(t)$ and LDA analyses are summarized in Table 1. All participants exhibited a significant decrease in mean RT for both the conjunctive and single-feature category learning tasks. Accuracy on the single-feature task was near ceiling for all participants on the first training day, indicating immediate mastery of the single-feature task. Accuracy in the conjunctive task was initially approximately 70% or better for all participants, improving to near ceiling accuracy by the end of training.

Capacity

$C(t)$ results are summarized qualitatively in Table 1 and depicted for Participant BS in Figure 2. Most participants exhibited limited capacity $C(t) < 1$ on at least the first two days. $C(t)$ then shifted to unlimited and super capacity $C(t) > 1$ on the third or fourth day of training. All participants exhibited super capacity configural mechanisms at the end of training.

Note that both AB and BS exhibited some early super capacity values on training days 1 and/or 2 together with higher error rates of 15-30%. This speed-accuracy tradeoff inflates $C(t)$ results. Both participants slowed their responses and reached ceiling accuracy, showing more limited $C(t)$ values before shifting to super capacity configural processing.

LDA

Linear discriminator performance was at least $A_z = 0.61$ for all participants on training days 1 and 2, indicating better-than-chance discrimination. Peak A_z values in Table 1 indicate the optimal performance achieved by the linear discriminator on each training day. All participants reached a peak $A_z \geq 0.74$. Maximum discriminator accuracy was reached on training day 6 or 7 for 3 participants, with Participant AB reaching maximum A_z on training day 5. Improvements in A_z were strongly correlated with the improvements in overall task accuracy for all participants (AB $r = 0.9447, p < 0.01$; BS $r = 0.788, p < 0.05$; DW $r = 0.9394, p < 0.01$; PG $r = 0.8852, p < 0.01$).

As shown in the upper panel of Figure 3, peak discriminating components form at a late training window over the first few training days, and over learning the LDA training window resulting in peak performance shifted earlier in time by

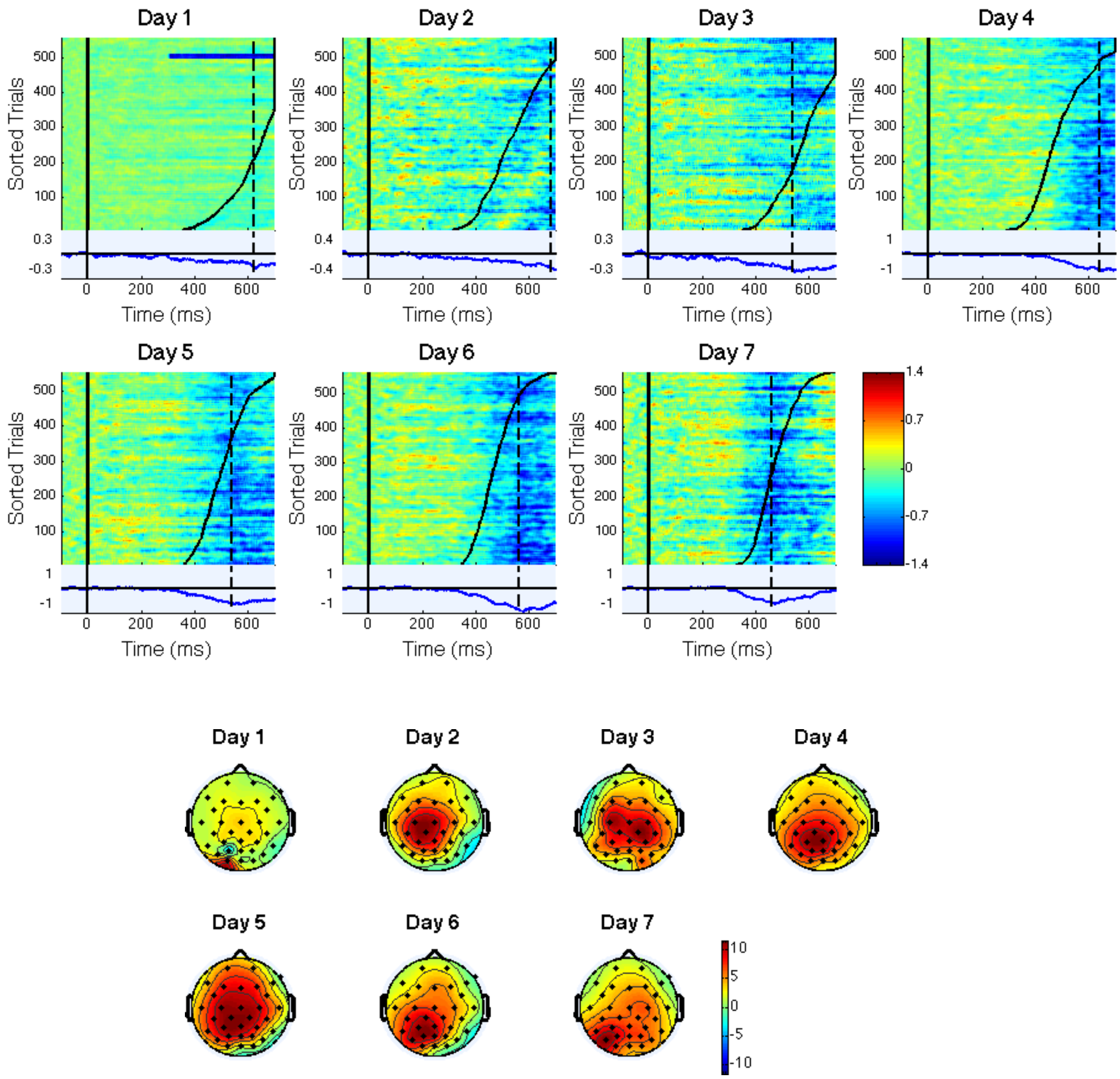

Figure 3: Top: Stimulus-locked discriminant component activity optimally differentiating Category 1 from Category 2 trials for Participant BS. Each line represents the component activity for a single Category 1 trial. The trial average difference component for Category 1 minus Category 2 is plotted below the component map. Empirical RT CDFs are superimposed on the component maps. Stimulus onset is at 0ms (solid vertical line). The dashed vertical line indicates the LDA training window onset time defining the optimally performing discriminator on each day. Bottom: Coupling coefficients of the optimal linear discriminator projected onto the scalp electrode array.

at least 100ms for each participant. Scalp projections of these peak discriminating components, like those shown in Figure 3 (bottom), indicate that sources strongly correlated with category discrimination shift to more posterior electrodes over training.

We note that in general, participants exhibited $C(t)$ improvements when $A_z \approx 0.65$. If we consider 0.65 to be a threshold of strong linear discrimination, we can track the earliest LDA training window on each training day at which the $A_z \geq 0.65$. These times are listed in the last column of Table 1. Note that N/A values indicate that the discriminator did not reach $A_z = 0.65$. For all participants, the linear discriminators reach the 0.65 threshold on the day before or the same day they began to exhibit reliable unlimited or super capacity performance. Initially the threshold LDA training windows were at 440ms to 540ms after stimulus onset, and these onset times also shift earlier by approximately 100ms or more. For all participants, day 7 threshold LDA training window onset times were approximately 250-400ms after stimulus onset.

Discussion

Our study is the first, to our knowledge, to employ LDA on single-trial EEG data on every day of a category learning experiment. With the LDA we found multiple neural indicators of learning, including improvements in discriminator accuracy and changes in both the timing of strong neural discrimination and the location of discriminating components scalp sources.

Capacity Coefficient results replicated our finding that configural learning is characterized by a qualitative shift from limited to super capacity (Blaha & Townsend, Under Revision). This confirms that people were not only learning to categorize these novel objects, but they developed configural processing mechanisms for the Category 1 object, as predicted.

LDA results exhibited several parallels to the behavioral findings. Overall accuracy correlated with human performance, showing learning-related improvements over training. We do note that LDA peak performance was not 100% like the behavioral data, indicating that both categories likely share many neural substrates. It may be that more extensive training, beyond our 3-week laboratory setting, would lead to even more discriminating neural performance.

Importantly, we find a key parallel to our $C(t)$ improvements in the time of both the peak and threshold LDA training windows. Both measures showed shifts to earlier times over training, consistent with improvements in processing efficiency which result from faster RT distributions. Changes in the threshold LDA training window in particular mirrored the shift from limited toward unlimited to super capacity performance. It could be that the Capacity Coefficient, measuring work-load efficiency, is evidence of a more discriminable neural signal associated with similar visual images or that neural discrimination reflects the efficiency of information processing. More work is needed to find a direct way to relate these two measures.

It is notable that the 0.65 threshold LDA training window after training occurs in a time frame similar to the N250 ERP component, which has been associated with the development of visual expertise indexed by subordinate-level categorization (Scott et al., 2006). The threshold discriminating components found here may reflect the use of neural mechanisms of expertise similar to those reflected in the N250 ERP amplitude differences found for this task (Blaha & Busey, 2007), providing converging evidence for the engagement of configural mechanisms developed by configural learning.

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