Attention and Pattern Consciousness Reorganize the Cortical Topography of Event-Related Potential Correlates of Visual Sequential Learning.

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Abstract

Statistical or sequential learning (SL) involves comprehending environmental patterns in which some items precede other items with a given likelihood. SL is thought to occur without attention or consciousness (or explicit knowledge) of the learned patterns and thus is sometimes considered to be implicit learning. However, this assumption is still debatable (Daltrozzo & Conway, 2014). We examined the role of selective attention and pattern consciousness (PC) in SL using event-related potentials (ERP) with healthy adults. Thirty-four participants (27 females, 18-49 years) performed a Flanker task to assess their level of selective attention, followed by a visual SL task while ERPs were recorded. Participants' level of PC was assessed via a questionnaire. In the SL task, participants viewed a sequence of different stimuli on the screen and were instructed to press a button as fast as possible, when they saw a target stimulus. They were unaware that: 1.) two predictor items were embedded in the sequence and 2.) the items predicted target occurrence with high or low probability. ERPs were time-locked to predictor onsets. The mean ERP between 200 and 700ms post-predictor onset revealed an interaction between target occurrence probability, PC, attention, and two scalp topographic factors. Post-hoc tests indicated that higher attention was related to a more rostral left lateralized effect under high PC and a left lateralization of SL ERP effects under low PC. These neural findings suggest that both attention and PC modulate SL.

Keywords: Implicit; explicit; left lateralization; statistical learning; language; automatic; controlled; sequence learning

Introduction

Sequential Learning (SL) is a process that enables people to perceive and learn statistically structured sequences in the environment (Lashley, 1951; Saffran, Aslan, Newport, 1996). For example, in spoken language, linguistic units such as phonemes, syllables, and words follow each other in a non-random sequence according to the language's phonology, phonotactics, semantics, and syntax.

Although SL has sometimes been regarded as a form of implicit learning (Perruchet & Pacton, 2006), there is also evidence that it may involve explicit processing (Daltrozzo & Conway, 2014; Turk-Browne, Junge, & Scholl, 2005; Wessel, Haider & Rose, 2012). An issue that is often skirted is whether SL should simply be dissected into attentional levels, stemming from the classic definition of implicit and explicit mechanisms (Shiffrin & Schneider, 1977) or whether this definition should be updated to involve PC. It might be advantageous to evaluate SL based on both attention and PC levels. PC is a dimension that has been explored in previous SL research, but not simultaneously with the attentional dimension (e.g., Daltrozzo & Conway, 2014). Even though PC and attention are known to affect the perception of structural regularities, their effect on SL may not be strictly identical. Attention to patterns may be necessary for SL to occur but attention alone may be insufficient without a certain level of PC. Thus, in SL tasks, the effect of attention and PC on SL may to some extent act independently of one another. In fact, a recent study attempting to dissociate between selective attention and PC for temporal order of visual events, demonstrated that attention and PC are functionally distinguishable constructs (Eimer & Grubert, 2015).

The Current Study

The purpose of the present study was to simultaneously explore the individual effects of attention and PC on SL. To this aim, we measured SL with a visual event-related potential (ERP) paradigm based on that used by Jost et al., (2015). The task involved the presentation of a series of visual stimuli wherein target stimuli could be predicted with varying levels of probability by the preceding stimulus. ERPs to two different predictors, reflecting high and low probability of being followed by the target, were compared across two levels of attention and two levels of PC.

According to recent research, SL shares mechanisms with language processing (Christiansen, Conway, & Onnis, 2012;

Conway et al., 2010; Uddén & Bahlmann, 2012). Assuming that language mechanisms are predominantly lateralized and that some of the shared mechanisms between language processing and SL are explicit, we predicted that increased attention would result in a higher activation of these explicit SL mechanisms, leading to a left-lateralization of SL ERP effects.

We further predicted that increased attention in conjunction with increased PC would correlate with more rostral SL ERP effects in the left hemisphere. This second prediction is in line with Uddén and Bahlmann (2012) who proposed a rostro-caudal organization of SL mechanisms in the left hemisphere in which greater sequence complexity and attentional load is associated with more rostral activity.

Method

Participants

A total of 34 participants (27 females, *M* = 22.4 years, *SD*= 6.3, 18-49 years) without any language, neurological, or psychological deficits from Georgia State University participated in the study for class credit. All participants were right handed according to the Edinburg Handedness Inventory (Oldfield, 1971) except seven (3 left-handed and 4 ambidextrous). All participants were native English speakers. None of them spoke, wrote, read, or understood Chinese. Participants were recruited from a local University online recruiting system and provided written informed consent to participate. The study was conducted in accordance with the guidelines of the Institutional Review Board of Georgia State University.

Procedure

Before the SL task (Figure 1), we assessed the participants' level of selective attention with the Flanker task (Eriksen & Eriksen, 1974). This task is commonly used to test response inhibition and selective attention (Fenske & Eastwood, 2003, Lavie et al., 2004). It measures a person's ability to detect relevant from irrelevant information. It is comprised of a central target (having a directional response-left/right) flanked by non-target stimuli whose direction matches that of the target (congruent) or is in the opposite direction of the target (incongruent). In the present study participants were required to provide the correct direction of a central target arrow while ignoring congruent (e.g., <<<<<) or incongruent (e.g., >><>>) flanker arrows. Typically, response times (RTs) for flanker incongruent trials are longer than for congruent trials – a difference known as the 'flanker effect' (Eriksen and Eriksen 1974). After the SL task, participants completed a questionnaire regarding their level of PC (Appendix). PC levels were obtained from an inter-rater agreement amongst three scorers from the participants' responses of the PC questionnaire (Inter-rater reliability: *Cronbach's alpha* = 0.965). Participants were each ranked as high or low (median split) based on their levels of attention and PC (Table 1). Thus each participant belonged to one of four groups: high PC and high attention (HCHA), high PC and low attention (HCLA), low PC and high attention (LCHA), and low PC and low attention (LCLA). Attention differed significantly between groups for each level of PC (Table1).

Table 1: Mean (SD) attention scores as measured by the Flanker task for attention and PC groups.

Pattern Consciousness		Attention			
		High	Low	*U*	*p*
	High	221 (156.28)	27 (24.27)	63	.001
	Low	143 (126)	-26 (63.99)	64	<.001

Attention measured by the mean response time (RT) difference between incongruent and congruent Flanker task conditions differed significantly between groups for each level of PC. [Two-tailed Mann-Whitney tests]

Stimuli

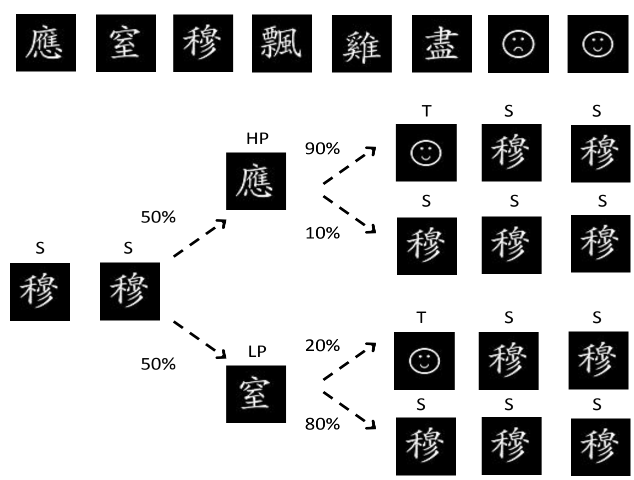

Figure 1: Visual SL task layout. [high probability, *HP*; low probability, *LP*; standard, *S*; target, *T*]

In the SL task, a sequence of visual items was presented on each trial (Figure 1). The sequence included a series of 'standard' stimuli (S) followed by a 'predictor' stimulus, and a 'target' (T) or standard stimulus. The target followed either a high probability predictor (HP) on 90% of trials or a low probability predictor (LP) on 20% of trials. For each participant, HP, LP, and S were pseudo-randomly assigned to 3 different Chinese characters from the 6 displayed on the top panel of figure 1, whereas T was pseudo-randomly assigned to one of the two smiley faces, to ensure target saliency. The participants' task was to indicate as fast as possible when the target occurred by pressing a button. Note that participants were given no prior knowledge of the predictor-target statistical contingencies, or even that there was a distinction among the different stimulus types. Instead, as was observed by Jost et al. (2015), the participant was expected to learn the predictor - target relationship (hereafter referred to as SL).

Each predictor condition (HP and LP) was presented 50 times. All sequence trials were continuous and randomly ordered across the two probability conditions, so that participants could not distinguish the onset or offset of one trial from another. Each participant was presented with a total of 100 trials (5 blocks of 20 trials each). A break of 30 seconds was given between each block.

We expected the Chinese characters to be perceived as abstract shapes by participants because they were unfamiliar with the Chinese language. By presenting items most likely perceived as abstract shapes, we expected to discourage any mental labeling of stimuli, shifting participants' reliance to a more implicit type of pattern learning.

Stimuli were presented electronically using E-Prime 2.0.8.90 software (Psychology Software Tools, Pittsburgh, PA), on a Dell Optiplex 755 computer. Every trial started with the presentation of a white fixation cross in the center of the screen over a dark background. Each visual stimulus was presented in white at the center of the screen on top of a dark background, displayed for 500ms with a stimulus onset asynchrony of 1000ms. A dark screen was displayed during the interstimulus interval of 500ms.

Electroencephalography Acquisition

Electroencephalography (EEG) was acquired from 256 scalp sites using an Electrical Geodesic Inc. sensor net (Figure 2) and was pre-processed using Net Station Version 4.3.1 with subsequent processing using custom scripts written in Matlab (version R2012b 8.0.0783, The MathWorks) and the EEGLAB toolbox (version 10.2.2.2.4a; Delorme & Makeig, 2004). Electrode impedances were kept below 50 kΩ. The EEG was acquired with a 0.1 to 100 Hz band-pass at 250 Hz and then low-pass filtered at 30 Hz. The continuous EEG was segmented into epochs -200ms to +1000ms with respect to the predictor onset. ERPs were baseline-corrected with the 200ms prestimulus data and averaged-referenced. Individual ERPs were computed for each participant, probability condition, and electrode. All experimental sessions were conducted in a 132 square foot double-walled, soundproof acoustic chamber.

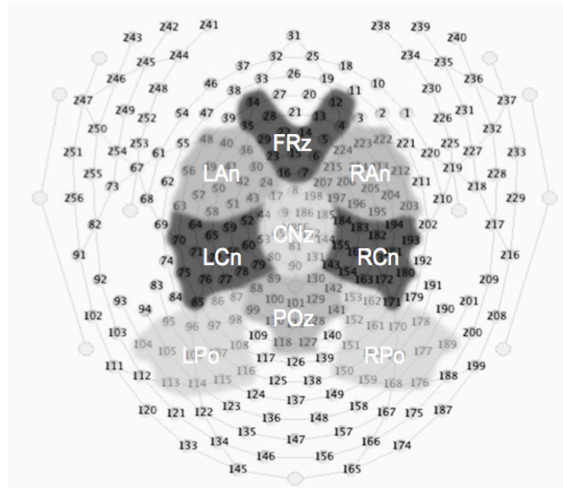

Figure 2: 256 sensors EEG net with the highlighted nine regions of interest.

Statistical Analysis

Statistical calculations were performed on the individual mean amplitude ERPs within 4 time-windows of interest (200-700ms, 400-800ms, 600-1000ms, and 800-1000ms) selected by comparing grand averages over each of the four participant groups (HCHA, HCLA, LCHA, and LCLA) to identify the main ERP variations due to the level of PC and the level of attention.[1] An unbalanced design due to the two between-participants factors (PC and attention) warranted the use of a linear mixed model (LMM) approach, which is suitable to analyze such data designs (West, Welch, Galecki, 2014).

To analyze the effect of cortical topography, nine regions of interest (ROIs, Figure 2) were defined: left (LAn), middle (FRz), and right anterior (RAn); left (LCn), middle (CNz), and right central (RCn); and left (LPo), middle (POz), and right posterior (RPo) regions. These ROIs defined the 3 levels of two topographic factors: Anteroposteriority (anterior, central, posterior ROIs) and Laterality (left, medial, right ROIs). For each of these 4 time-windows of interest (see previous footnote) a LMM was applied with: (1) fixed effects: probability condition (2 levels: HP and LP), probability condition X PC (2 levels: "high" and "low" PC), probability condition X Attention (2 levels: "high" and "low" attention), probability condition X PC X Attention, probability condition X PC X Attention X Anteroposteriority (3 levels: anterior, central, and posterior ROIs), probability condition X PC X Attention X Laterality (3 levels: left, medial, and right ROIs), and probability condition X PC X Attention X Anteroposteriority X

Results obtained from the analyses of 400-800ms, 600-1000ms, and 800-1000ms time windows were similar to those obtained from the 200-700ms window. Therefore, we report only the results obtained with the 200-700ms window

Laterality; (2) random effects: PC and Attention. Pairwise comparisons were Šidák corrected for multiple comparisons.

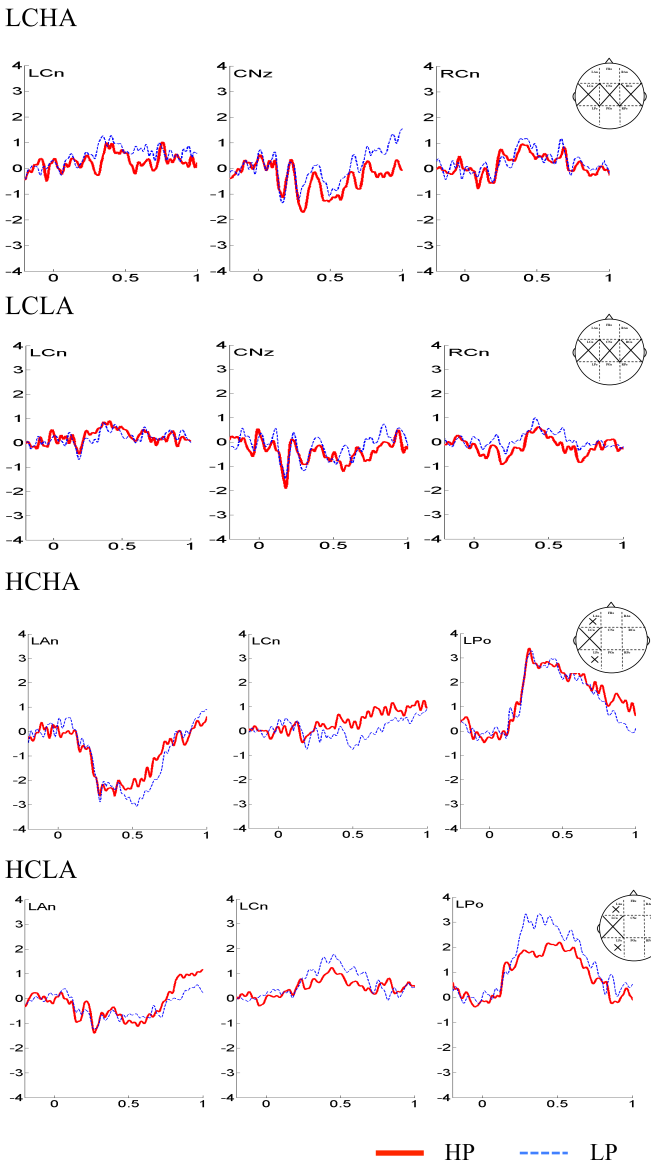

Figure 3: Grand average ERPs over the 4 groups: LCHA, LCLA, HCHA and HCLA. All are in response to the high probability condition (*HP*, red solid line) and low probability condition (*LP,* blue dotted line) (vertical axis: electric potential in µV, positivity upward; horizontal axis: time in seconds). Schematic heads: crosses indicate the corresponding ROIs.

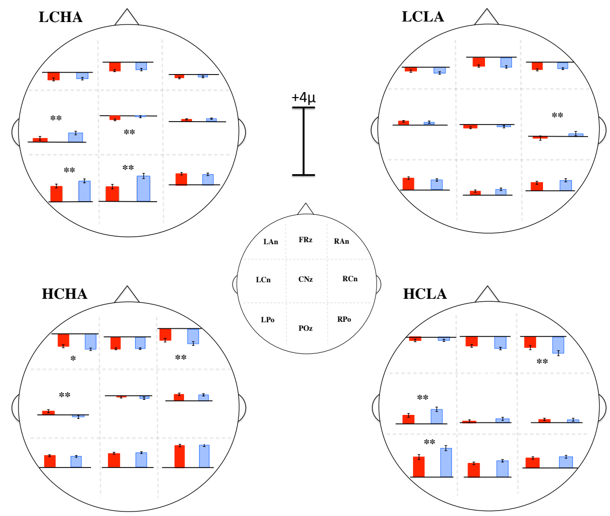

Figure 4: Means with standard error bars of ERPs in the 200-700ms time window for each ROI in each subgroup of participants [high probability condition (*HP*, uniform red bar); low probability condition (*LP*, dotted blue bar). Vertical scale displayed in the center of the figure: electric potential in µV, positivity upward, **=p <.01; * = p <.05].

Behavioral analyses were conducted across all four groups to assess influence of PC and attention. Similar to the ERP data analyses, RTs were analyzed with a LMM applied with: (1) fixed effects: probability condition (2 levels: HP and LP), probability condition X PC (2 levels), probability condition X attention (2 levels), probability condition X PC X attention and (2) random effects: PC and attention. Pairwise comparisons were Šidák corrected for multiple compare

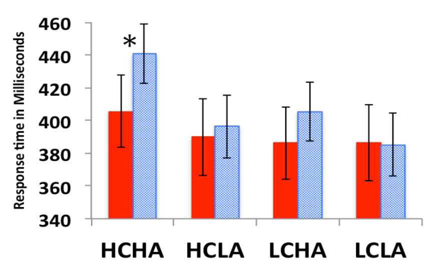

Figure 5. RT across the four performance groups for the high (uniform red) and low probability condition (dotted blue); [* = p <.05].

Results

Figure 3 displays the grand average ERPs across LCHA and LCLA participants for each probability condition, within the 200-700ms range. Visual inspection indicates that the difference between the ERP to HP and LP conditions (i.e. the SL ERP effect) shifts from a right central effect in the low attention group (LCLA) to a left and medial effect in the higher attention group (LCHA).

Figure 3 also displays the grand average ERPs across HCHA and HCLA participants for each predictor condition, within the 200-700ms range. Visual inspection indicates that the SL ERP effect shifts from a more caudal - centro-posterior - effect in the low attention group (HCLA) to a more rostral – fronto-central - effect in the higher attention group (HCHA).

A LMM performed on mean ERPs within the 200-700ms window indicated an interaction between probability condition, attention, PC, and the two topographic factors (Anteroposteriority and Laterality) [$F(32, 1466.81) = 4.23$, $p < .001$]. Posthoc tests revealed significant SL ERP effects in a subset of the 9 ROIs that varied across groups (Figure 4). A LMM performed on RTs indicated faster responses to HP (M = 406ms) than to LP (M = 441ms) demonstrating SL in the HCHA group [$F(1,34) = 5.18$, $p = 0.029$] (Figure 5). Trends in other groups suggested SL decreases as attention and PC decreased.

Grand averaged ERPs in Figure 3 indicate variations in ERP effects according to the lateral dimension (LCLA vs LCHA) and the rostro-caudal dimension (HCLA vs. HCHA) some of which are significant as indicated in Figure 4.

Discussion

We explored the effects of attention and PC on the neural correlates of visual SL using ERP. Our main findings are that: (1) under low PC, increased attention resulted in a left lateralization of the SL ERP effects; and (2) under high PC, increased attention induced more rostral left-lateralized SL ERP effects.

The left-lateralization of SL ERP effects with increased attention suggests that shared mechanisms between SL and language processing (Christiansen et al., 2012; Conway et al., 2010; Uddén & Bahlmann, 2012) are likely to be partly explicit. Thus, the larger left-lateralized SL ERP effects with increased attention could be a correlate of a greater activation of these explicit mechanisms that are shared with left-lateralized language processes.

Alternatively this left lateralization of SL ERP effects with attention could be due to left-lateralized attentional mechanisms that engage in temporal processing. Emerson, Daltrozzo and Conway (2014), reported larger left lateralized SL ERP effects with higher musical expertise using a SL ERP paradigm similar to ours. Several studies have suggested that variation in cognitive processing of temporal structures with higher musical expertise may not be due to musical expertise alone but possibly due to a higher ability in musicians to focus their attention on temporal patterns, compared to non-musicians (Parbery-Clark et al., 2011; Strait et al., 2010). Thus, left lateralization of our SL ERP effects with attention could be due to higher attention to the temporal sequence activating SL mechanisms that are common between SL and music processing.

In addition to an overall increased left lateralization with higher attention, we also found more rostral left lateralized SL ERP effects with higher attention in participants with high PC. Udden and Bahlmann (2012) proposed that the left inferior frontal gyrus is part of a general rostro-caudal abstraction gradient in the left pre-frontal cortex, in which complex sequences such as sentences are predominantly processed by more rostral mechanisms, while simpler sequences such as syllables that consist of single words would be more caudally distributed. Importantly, this dimension of complexity is partially expected to correspond with the level of attention, at least in the language domain with sentence-level processing recruiting more attentional resources than word-level processing (Daltrozzo, Wioland, & Kotchoubey, 2012). Taken together, our results seem to confirm the rostro-caudal model of SL, by Uddén and Bahlmann (2012), if we assume that their dimension of sequence complexity is related to attentional capacity and cognitive control.

Furthermore, current RT data indicated that the high PC-high attention group was better at learning the predictor-target rules than the low PC-low attention group, demonstrating that some unique combination of PC and attention, shape SL. Also, the present quasi-experimental study is essentially correlational, as we compare groups of participants with varying attention and PC. Hence, we can only account for relationships between SL ERP effect of cortical topography, attention, and PC without attributing cause-effect relationships between these variables.

In conclusion, our findings suggest that the cortical organization underlying SL depends heavily on two separate cognitive dimensions that have often been confounded in previous SL research (Daltrozzo & Conway, 2014), or at least have not been tested independently, namely the levels of attention and of PC. Currently, it is unclear why attention modulates SL differently across levels of PC. This likely pertains to a more general issue, that which highlights the exact relationship between attention and PC and their influence on the cortical assembly underlying SL and language.

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Appendix

Questionnaire assessing the level of PC:

1. Think about the task with Chinese characters you did. Did you notice anything about the Chinese characters? Tell me about your perception of the task. [Verbatim record]

2. Do you think the Chinese characters were occurring randomly? [If the participant says no, ask to explain how the characters were non-randomly displayed.]
3. Was there a pattern or anything regular in the order that the Chinese characters were presented?
4. Was there a Chinese character that usually came before the target (the smiley face you were looking for)?
5. If you noticed a pattern, at what point did you notice it? Before 1st break, after 1st break, after 2nd break, after 3rd break, after 4th break?
6. Did you get tired during the task? At what point did you start getting tired?
7. Was the task too long?

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