Personality and Individual Differences 118 (2017) 29–38

Contents lists available at ScienceDirect

Personality and Individual Differences

journal homepage: www.elsevier.com/locate/paid

Brain states predict individual differences in perceptual learning

Alexandra Muller-Gass [a,b,c,*], Matthew Duncan [a], Kenneth Campbell [b]

[a] Defence Research and Development Canada, Toronto Research Centre, Canada
[b] University of Ottawa, School of Psychology, Canada
[c] Canadian Forces Health Services, Directorate of Mental Health, Canada

ARTICLE INFO

Article history:
Received 6 February 2017
Received in revised form 24 March 2017
Accepted 29 March 2017

Keywords:
EEG
Event-related potentials (ERP)
Perceptual learning
Individual differences
Automaticity
Inhibition
Alpha rhythm
P3b

ABSTRACT

Brain states dynamically change with learning and these changes vary widely among individuals. Recent research proposes that electrophysiological measures of brain states can also predict individual variability in successful learning. This study was conducted to examine neural mechanisms of learning and neurophysiological indicators that predict success in a perceptual learning task. EEG was recorded over 20 blocks of trials while subjects learned to categorize a complex visual stimulus that required integration of multiple physical dimensions for successful categorization. For the analysis, final performance scores were used to median split subjects into high and low learners. By the 6th block, high learners began to diverge, eventually achieving 80% accuracy while low learners remained only nominally above chance. ERPs to the visual stimulus revealed a P3b that was significantly larger in high learners even before performance differences had emerged, but that did not vary with learning. Power spectral analyses showed that resting-state alpha was larger for high learners both before and during learning. Finally, alpha power increased for high but not for low learners as learning progressed. These results show that electrophysiological measures, especially alpha power, may not just reflect the learning process but also serve as predictors of eventual learning performance.

1. Introduction

Learning is a fundamental cognitive activity the principle result of which is ultimately a change in the way a person responds to the environment. Learning itself represents a broad category of investigation which is often characterized by the kind of information learned (e.g. perceptual learning) or the process by which learning is achieved (e.g. implicit learning). Perceptual learning can be defined as an improvement in the ability to perceive which is achieved through repeated sensory experience. It is a form of implicit learning, in which learners often cannot easily verbalize how and what it is that they learned. However, despite intact sensory and cognitive function there is still a large amount of variability in perceptual learning among individuals, with some showing great success and others little to no learning. While much research has shown that learning is a process that ultimately affects brain function and organization, recent electrophysiological work has suggested a possible explanation for observed individual differences in perceptual learning. Namely, the brain state the learner brings to the task itself can also affect learning by facilitating or hindering the learning process. These studies have recorded changes in brain states associated with the learning process and remarkably, predicted learning well before performance evidence of this learning was apparent (Freyer, Becker, Dinse, & Ritter, 2013; Mathewson et al., 2012).

In the present study, we examine changes in measures of brain states, specifically the electroencephalogram (EEG) and event-related potentials (ERP), as subjects gained (or not) proficiency in a perceptual categorization task. The ongoing electrical activity of the brain, the EEG, consists of a series of oscillations with different frequencies and amplitudes that vary based on mental state. ERPs are minute changes in the EEG that are elicited by an external physical stimulus or internal cognitive events. The ERP waveform consists of a series of negative- and positive-going components shown to reflect different aspects and stages of information processing and vary based on the extent of processing. Both EEG oscillations and ERP waveforms exhibit considerable individual differences in their fluctuations and patterns, and it is conceivable that learning variability could in part be related to these particular brain signatures. Although most electrophysiological studies of learning have focused on changes after learning is complete, such an approach cannot reveal how electrophysiological activity dynamically changes to reflect improvements in perceptual performance or whether a pre-existing neurological disposition can affect performance. In order to do so it is necessary to track brain activity throughout the entire learning process.

* Corresponding author at: Canadian Forces Health Services Group Head Quarters, Directorate of Mental Health, 1745 Alta Vista Dr., Ottawa, ON K1A 0K6, Canada.
E-mail address: Alexandra.Muller-Gass@drdc-rddc.gc.ca (A. Muller-Gass).

http://dx.doi.org/10.1016/j.paid.2017.03.066
0191-8869/

1.1. EEG oscillations

Of particular importance to learning is the 8–12 Hz alpha oscillation, discovered in the very first EEG recordings from the human scalp when subjects were resting, with their eyes closed (Berger, 1929). Early investigations noted that simply opening the eyes can cause a marked attenuation (or desynchronization) of alpha and for this reason, many concluded that alpha reflected an "idling" state during which the cortex is not engaged in a task (see Pfurtscheller, Stancák, & Neuper, 1996 for a review). By contrast, high attention and vigilance is associated with low alpha power (Thut, 2006). The functional role of alpha is however still debated and recent work has suggested that changes in alpha rhythm cannot simply be explained by global fluctuations of attention or vigilance. Instead, an inhibition role has been emphasized, with alpha power reflecting a top-down inhibition of processes that are not relevant to the task (Jensen & Mazaheri, 2010; Klimesch, Sauseng, & Hanslmayr, 2007; Sigala, Haufe, Roy, Dinse, & Ritter, 2014). Considering the complexity of the alpha rhythm, alpha may have different roles depending on the specifics of the task.

Changes in alpha activity have recently been intimately linked to both short- and long-term learning. Hamamé, Cosmelli, Henriquez, and Aboitiz (2011) employed a complex visuo-spatial search task, and trained subjects on this task for a 1 h session each day over 5 days. During the presentation of the visual stimuli, alpha power gradually decreased, as would be expected with active processing of the complex stimulus changes. Desynchronization however dissipated over the last two training sessions and alpha power thus increased as training progressed. The alpha enhancement would be consistent with successful learning and the need for less attention and resources to be devoted to the task. Similarly, Bays, Visscher, Le Dantec, and Seitz (2015) employed a complex visuo-spatial search task and found evidence of an increase in alpha power following learning. Subjects were trained on this task for 1 h/day over an 8 day period. EEG was recorded on the first day and one day after the final training session. They found that the alpha power attenuated following the onset of the visual stimulus (or alternatively, alpha desynchronization increased) with training on the task. Furthermore, they found that training resulted in increased alpha power during the pre-stimulus period, a 1 s period prior to the onset of the stimulus. Again, this later effect may be related to the gradual automaticity of processing associated with efficiency in the learning of the task. Freyer et al. (2013) employed a somatosensory perceptual learning task in which subjects passively learned a tactile discrimination task through repetitive stimulation. Discrimination performance on the task was greatly improved with stimulation; and importantly, the higher the alpha power was during a rest period prior to stimulation, the larger the improvement on task performance after stimulation. Some studies have also examined brain state correlates of learning during continuous learning tasks such as video games. In Maclin et al. (2011), subjects learned to respond in a complex visual computer game, and the results showed that an increase in alpha power at central sites following stimulus presentation was associated with learning. In another study employing a real-time video game task, Mathewson et al. (2012) found that those who eventually learned the game well showed larger alpha power over frontal sites very early in training.

1.2. ERPs

Several studies have examined the effect of learning on early processing, as reflected by ERP components occurring shortly after stimulus presentation and well before actual decision-making. A negative-component occurring at about 200 ms after stimulus onset, termed the N2pc, has been demonstrated to increase in amplitude during visual search tasks as the subject learns to attend to a relevant feature occurring among many others (An et al., 2012; Hamamé et al., 2011; Qu, Hillyard, & Ding, 2016). However, this N2pc effect is specific to visual search tasks and is not known to generalize to other types of learning. A few studies have investigated another candidate ERP as a correlate of learning; this ERP, the P3, has been the subject of a considerable number of studies. It was first described by Sutton, Braren, Zubin, and John (1965) as occurring following the detection of a rare, task relevant stimulus. Its latency can occur as early as 300 ms (and for this reason, is also often called P300) when targets are easily discriminable but typically occurs from 400 to 600 ms in more difficult and complex tasks.

The amplitude of P3 has often been associated with the updating of working memory.[1] The learning process obviously requires the updating of memory based on feedback about the correctness of the decisions. Barceló (2003) employed a modified Wisconsin card sorting task in which subjects had to learn the correct concept appearing on the card through a trial-and-error process. They examined ERP components time-locked to the perception of the cards to-be-categorized, and changes associated in this perception as learning progressed. Although the correct categorization could be learned within a few trials, they noted that a small positivity, that they termed the P3a, occurring at about 200 ms was larger, albeit non-significantly, on stay (keep the concept) than shift (change the concept) trials. On the other hand, a later, parietal maximum positivity, that they termed P3b, occurring from 400 to 800 ms was significantly larger on stay than shift trials. Thus, as the concept was gradually learned, the amplitude of the P3b became larger. In the Hamamé et al. (2011) task involving long-term learning of complex visuospatial features, a P3b was observed to both equally probable targets (containing the key feature) and nontargets. This P3b also gradually increased in amplitude as subjects learned the discrimination over five days. Maclin et al. (2011) and Mathewson et al. (2012) also recorded a P3b to task relevant visual stimuli contained within a complex computer game. However, the P3b proved to be only a weak predictor of individual improvement in video game performance, although the authors noted that this may be due to latency jitter related to the timing of the stimulus presentation associated with recording in a continuous real-world task.

1.3. The present study

Perceptual categorization tasks provide an ideal methodological paradigm for the study of perceptual learning in a discrete trial context. In such tasks, subjects learn to classify perceptual stimuli, typically visual, into two or more categories over the course of hundreds of trials. The stimuli are constructed to vary across 2 or more physical dimensions and require subjects to integrate the dimensions for proper classification. The task can be cognitively complex, produces gradual learning, and like many real world learning situations is implicit (i.e., procedural) as subjects are usually not able to adequately verbalize the rule learned to classify the stimuli. An additional, but important, characteristic of perceptual learning in categorization tasks is that they often accommodate a wide variety of individual differences in both asymptotic performance and in rate of learning (see Ashby, Ell, & Waldron, 2003; Zeithamova & Maddox, 2007). The present study records EEG and ERPs while subjects engage in a visual perceptual categorization task. The task was piloted and adapted in such a way to be very difficult, and produce considerable learning variability among individuals. Based on previous studies, it was expected that the P3 elicited by the visual stimuli would become more prominent as subjects improved their task performance. It was also expected that the EEG, in particular the alpha activity, evoked during the pre-stimulus resting periods would predict eventual success in learning the task.

[1] Because of its association with decision-making, Stelmack and colleagues have frequently employed P3 in their studies of individual differences in cognitive abilities (see for example, McGarry-Roberts, Stelmack, & Campbell, 1992; Beauchamp & Stelmack, 2006; Sculthorpe, Stelmack, & Campbell, 2009).