Characteristic Alpha Reflects Predictive Anticipatory Activity (PAA) in an Auditory-Visual Task

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Abstract. Several lines of evidence suggest that humans can predict events that seem to be unpredictable through ordinary sensory means. After reviewing the literature in this controversial field, I present an exploratory EEG study that addresses this hypothesis. I used a pattern classification algorithm drawing on EEG data prior to stimulus presentation to successfully predict upcoming motor responses that were constrained by the upcoming stimulus. Both the phase of peak alpha activity and overall amplitude at ~550 ms prior to the presentation of the stimulus were useful in predicting the upcoming motor response. Although these results support the idea that brain activity may reflect precognitive processes in certain situations, due to the exploratory nature of this study, additional pre-registered confirmatory experiments are required before the results can be considered solid. Implications for creating a closed-loop predictive system based on human physiology are discussed.

Keywords: Predictive anticipatory activity · Presentiment · Precognition · Prospection · EEG · Alpha · Auditory-visual

1 Introduction

Many organisms can use associations from past experiences to help predict future ones. For instance, planarian worms that have been trained to expect electrical shock following a light burst will demonstrate a conditioned response to the light alone [1]. Here we discuss some neurophysiological correlates of a different kind of prediction – one that does not seem to be based on inferences from past experiences. This kind of prediction is known as *precognition* – the beyond-chance prediction of future events

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The original analysis and some of the results described in this paper was registered with the Koestler Parapsychology Registry at http://www.koestler-parapsychology.psy.ed.ac.uk/Doc-uments/Study_Results_1004.pdf. Further, that document briefly describes how the initial prediction from the first 20 participants was assessed in the second 20 participants, and was not upheld (unless the alpha level for significance was relaxed). The results shown in more detail here are from a combined analysis of data from all 40 participants. Thus, any meta-analysis including this manuscript should not include the data registered there, to avoid data duplication.

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that are not predictable through ordinary means. In humans, the physiological analogue to precognition has been called *presentiment* [2], or more recently, *predictive anticipatory activity* (PAA; [3]). After a brief review of the behavioral precognition and PAA literature, I will describe an EEG experiment in which I used characteristic alpha measures to examine PAA in an auditory-visual task. While we do not currently understand the mechanisms underlying PAA, the results of this experiment add to converging evidence that it may be possible to engineer a closed-loop system drawing on PAA or related phenomena to predict seemingly unpredictable future events.

2 Background

Given that we normally experience a linear order of events in time, it seems reasonable that our minds or bodies could accurately predict future events only if those future events can be inferred from the past. On the other hand, given that we know about the order of events in time is largely based on our conscious perceptual experiences, one also might consider that nonconscious processes (of which we are not normally aware) may have access to what we call the "future" (e.g., [4, 5]).

Regardless, it is safe to say that if an organism can predict a future event with any level of accuracy beyond chance, using whatever means, this ability is likely to be adaptive. Whether that event is predictable based on our present-day understanding of time may not eventually turn out to be of practical importance. Instead, what I suggest is important for our survival is the ability to harness any sort of predictive ability, regardless of its source, and use it to predict events such as strokes, terrorist attacks, explosions, and violent riots [6]. Via the process of this harnessing project, we may better understand the unfolding of events in time.

The evidence that both human behavior and physiology are influenced by seemingly unpredictable events in the future has recently been highlighted in two meta-analyses. Behavioral evidence for precognition in humans was recently examined in a meta-analysis including 90 implicit precognition experiments examining the hypothesis that even when participants aren't asked directly about future events, behaviour in the present is related at a level beyond chance to randomly selected future events that are not known in the present by experimenters or participants in the experiments [7]. While the overall effect was highly statistically significant, it was also small. Interestingly, an admittedly post-hoc but nonetheless revealing analysis of the data showed that the overall effect was carried by the subset of the experiments in which participants were asked to use less deliberation ("fast-thinking" behavioural systems [8]). This subset of the experiments had a bigger, significant overall effect, whereas the other subset (using "slow-thinking" systems) was smaller and not statistically significant. This analysis suggests that conscious, deliberative control may obscure information about future events. In support of this idea, I took a precognition experiment that originally required extended deliberation, and after consulting with the experimenter's designer (Daryl Bem), I created a low-deliberation version of the experiment, which revealed a significant precognitive effect for events that would occur minutes in the future [9]. I am currently conducting an attempted replication of this effect. Further supporting the idea that behavior precognition represents a real, albeit unexplained effect, experiments in birds [10] and planarian worms [11] have revealed statistically significant differences in predictive behavioral changes in these animals prior to two classes of randomly selected behavioral stimuli.

Physiological precognition, otherwise known as predictive anticipatory activity or PAA, was examined in a meta-analysis including 26 PAA experiments in humans [3]. The meta-analysis examined the hypothesis that physiology in the present is related at a level beyond chance to randomly selected future events that are not known in the present by experimenters or participants in the experiments. The meta-analysis found a statistically significant small-to-medium overall effect, and spurred some reasonably friendly debate [12, 13].

3 Motivation and Study Overview

In the abstract and conclusion of the PAA meta-analysis, we included the following sentence: "The cause of this anticipatory activity, which undoubtedly lies within the realm of natural physical processes (as opposed to supernatural or paranormal ones), remains to be determined." The dual aims of understanding the natural physical processes underlying PAA and, in order to do so, enhancing the signal-to-noise ratio of the effect, are what drove me to undertake the PAA experiment using EEG that I describe here.

To understand the context of this experiment, it is important to know that Libet [14] and later others [15, 16] found neurophysiological signals called readiness potentials, which are generally considered to be neurophysiological reflection of unconscious decision-making processes tied to upcoming choices. Further, Matthewson et al. [17] showed that EEG activity in the alpha range (7.5–12 Hz), especially alpha phase, predicts whether an upcoming near-threshold visual stimulus will be detected or not, which was reported via a motor response. It seemed possible that perhaps both phenomena could be interpreted as PAA signals that predict upcoming motor responses, especially given that there is tentative evidence that precognition may be associated with alpha activity (for review, see [18]). To examine this idea, I designed a task in which the motor response is not a free choice, as it is in a traditional readiness potential experiment, but instead is constrained according to task directions about which of two buttons to press in response to randomly selected auditory and visual stimuli. Then I analysed current-source density transformed ERPs and EEG alpha activity that occurred prior to the software's decision about which stimulus to present to the participant, within the time frame of readiness potentials termed "type I" as originally found by Libet [14], to determine whether this activity could predict the upcoming button press.

4 Brief Methods

4.1 Hypothesis

The hypothesis of this study was that future motor responses to randomly selected auditory and visual stimuli could be predicted from brain activity that occurred prior to the selection of the stimuli.

4.2 Participants

Forty participants, ages 18–26, completed the study in two groups of 20. All participants were right-handed native speakers of English, and none had been diagnosed with neurological deficits. Some participants received course credit in exchange for their participation, while others received payment ($10/h for 2 h). All participants signed a consent form, describing procedures approved by the Northwestern University Institutional Review Board.

4.3 Task and Stimuli

The task was a speeded response task coded in Presentation software, in which I asked participants to press the left key of a computer mouse after seeing a white number "1" on a dark computer monitor or hearing a low-pitched tone (250 Hz) over headphones, and to press the right key of a computer mouse after seeing a white number "2" on the dark computer monitor or hearing a high-pitched tone (1 kHz) over the headphones (Fig. 1). All button presses were to be made with the right hand. I wanted participants to monitor attention in more than one sensory system because I suspected that this could ensure that they did not fall asleep as they did the task (a problem I had had with other EEG studies). Further, the auditory-visual nature of the task allowed me to test a different hypothesis that I do not explore here.

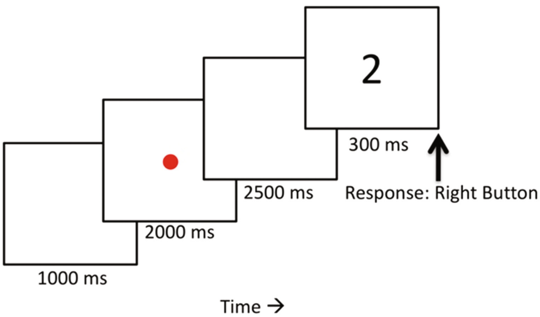

Fig. 1. Schematic showing timing and example of the correct response on a sample visual trial of the auditory-visual task, as it would appear to a participant.

All stimuli were randomized according to a pseudorandom number generator, which selected from the four possible stimulus types with equiprobability. The selection of the stimulus type was made just prior to the beginning of the pre-stimulus delay.

The order of events in the task and their durations were:

(1) black screen with no visual or auditory input (1000 ms),
(2) presentation of a red fixation dot in the center of the screen (2000 ms),
(3) random selection of stimulus type (with no display or indication of type),
(4) pre-stimulus delay with no visual or auditory input (2500 ms),

(5) presentation of the selected visual stimulus alone or auditory stimulus alone (300 ms),
(6) [user responds according to task requirements; all records with response times > 700 ms removed from analysis],
(7) return to 1.

4.4 Procedure

After the participant read and signed the consent form, I fitted 64 active EEG electrodes (BioSemi cap) to the participant's scalp. I explained that I was interested in understanding how neural activity as recorded by EEG electrodes could be related to expectation of future events. I did not discuss precognition. I told participants that while I knew this was an easy task, they should try to be as accurate and as fast in their responses as possible. The goals of this instruction were: first, to help participants attend to the task and not fall asleep, and second, to push response times into the domain in which fast-thinking processes could dominate. I also asked participants to blink during the presentation of the red fixation dot and to withhold blinking after that until they responded, because this would produce fewer eye movement artifacts during the 2.5 s leading up to the stimulus presentation.

The first 20 participants performed 120 trials of the task and the second 20 participants performed 100 trials of the same task. The reason for the change in the number of trials in the second group of participants was that I wanted to shorten the duration of the experiment because several of the first 20 participants had complained about boredom, and the analysis data from the initial 20 participants suggested that 100 trials was enough to obtain the effect. All analyses shown here were derived from the first 100 trials of all 40 participants.

4.5 EEG Analysis

I recorded EEG with a 64 + 8 active-electrode (Biosemi) system, using a 1024-Hz sampling rate and bandpass filtering between 0.1 and 100 Hz. Using Matlab (EEGlab Toolbox), I re-referenced data offline to a nose electrode. I baselined each value in the 2500-ms pre-response trace preceding a correct response to the average of the first 500 ms of that 2500-ms pre-response trace, and removed blinks and movement artifacts using standard methods. I used current-source density transformation in Matlab to improve resolution (CSD Toolbox Version 1), and performed all remaining analyses on the CSD-transformed traces. After examining the data, I focused on two different dependent variables that seemed to predict upcoming motor movements: mean (within-participant, across-trial) CSD trace magnitude, and phase of the mean CSD trace (within-participant, across-trial) at each individual's peak alpha frequency in the CSD traces. Each were calculated twice for each participant; one time each for the trials preceding right- and left-button presses. To calculate the mean CSD trace magnitudes for each person at each electrode and for each of the two response types, I averaged the values of CSD traces in 25 ms intervals between $\sim$1850 to $\sim$1975 ms ($\sim$650 to $\sim$525 ms prior to stimulus presentation; times approximate because analysis was done on the points sampled at 1024 Hz). Thus for each of the response types, each person had 320 CSD trace magnitudes (64 electrodes $\times$ 5 epochs). I calculated peak alpha activity by first using a Fast Fourier Transform on each trace to find the frequency with greatest energy in the alpha range (7.5–12 Hz), then using a Butterworth filter to create a trace containing just that isolated frequency. Then for each electrode for each participant and each response type, I calculated the mean CSD trace within each participant, finally calculating absolute phases of this mean trace at the same 25 ms intervals (calculated every 25 ms between $\sim$1850 and $\sim$1975). Thus for each of the response types, each person had 320 CSD peak alpha phase values.

4.6 Pattern Classification

I used a random forest pattern ensemble pattern classification algorithm to objectively determine which of the dependent variables were best able to classify the future motor response (left or right button press). More details about this algorithm are available in my previous work [19], but briefly, the algorithm performs a series of analyses using decision trees to separate the data, and it includes a generalization test in which it uses a subset of the data as a training dataset and then tests on the remaining portion of the data (i.e., out-of-bag error estimation). Thus, only the error rate based on attempts at classifying the upcoming response using the instances that are not used during the training phase are reported as the final, or "generalization" error rate. It also allows for post-test querying to determine which features are most important in each classification attempt. The classifier was run with 640 sets of dependent variables for each of the response types, for each of the 40 participants (see Sect. 4.5 *EEG analysis*). The classifier was executed using the actual data versus a scrambled version of the same data to create a fair comparison, given that there were many dependent variables. This scrambled version was created on each run of the classifier by randomly selecting 50% of the left-button trials and renaming them as right-button trials, and vice versa. I ran the classifier 1000 times each, for the original data and the scrambled version of the same data, and recorded the generalization error rates for both datasets and the most important features for the original data.

5 Results

Here I report only the EEG results of this study; the behavioral results were not remarkable in relation to the present hypothesis. Grand means of CSD-transformed traces for correct trials showed a differential time course depending on the appropriate response to the upcoming stimulus (Fig. 2). The differential activity (black lines) deviates from zero primarily in the left-frontal region, suggesting that in the time domain, scalp electrodes in this region are best at separating future right- from left-button presses during time prior to stimulus presentation.

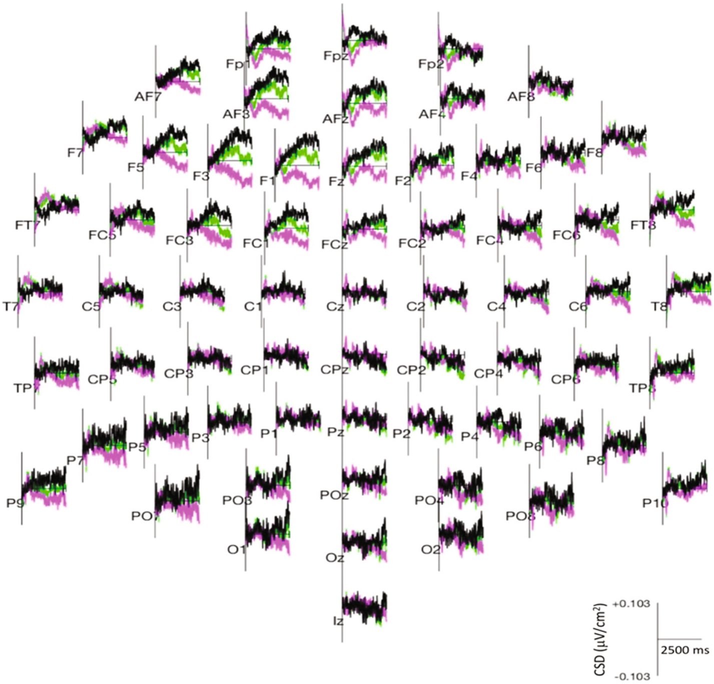

Fig. 2. Grand mean CSD traces for the 2500-ms pre-stimulus period (including the 500 ms baseline period) for correct trials on the auditory-visual task (N = 40 participants). Left upcoming response is indicated by green (middle trace); right upcoming response is indicated by pink (bottom trace); the difference is indicated by black (top trace). Correct responses were tied to the stimulus presented at 2500 ms, according to task instructions. (Color figure online)

Our statistical method allowed us to compare two distributions of generalization errors rate across 1000 attempts at classification of the across-participant data (Fig. 3). A distribution tail-test comparing classification error rates based on data presented in the original order versus data presented in scrambled orders gave a statistically significant result ($p < 2.5 \times 10^{-6}$). The classification method allowed us to determine the relative criticality for the 10 most critical electrodes and time points for each of the two dependent variables with the data in the original order; these were the three electrodes that were calculated by the classifier as the most necessary to produce robust classification (i.e., without these electrodes, classification all but failed). Averaging the relative criticality weighting of these electrodes over the 1000 classification attempts indicated that, on average, the most critical electrodes for the CSD-trace magnitude data were in the midline-to-left-frontal region (Fig. 4, left), and the most critical electrodes for the peak alpha-phase data were in the midline-to-right-parietal region, with some left-frontal involvement (Fig. 4, right). Further, the activity at the most critical electrode for both the CSD-trace magnitude data and the peak alpha phase data occurred at $\sim$550 ms prior to stimulus presentation ($\sim$1950 ms), suggesting that this time point contains more information about the future response than any other tested timepoint.

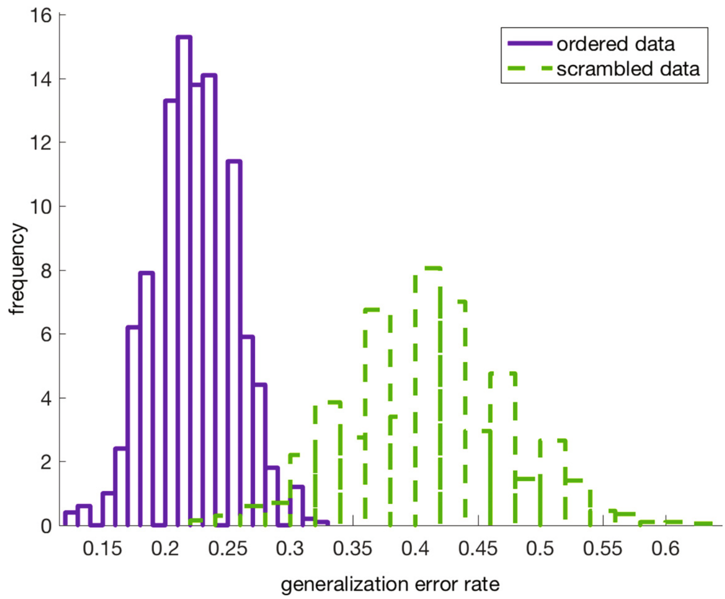

Fig. 3. Generalization error rate histograms for ordered data (purple; solid line) and scrambled data (green; dotted line). Chance performance is at 0.5, but the important comparison is the lack of overlap between distributions. (Color figure online)

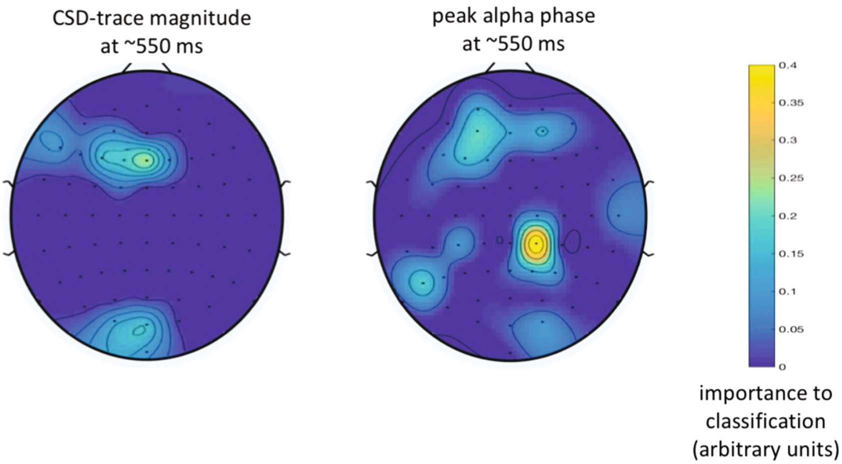

Fig. 4. The most critical features among the two types of dependent variables for predicting future left versus right responses. Hotter colors indicate higher importance. (Color figure online)

6 Conclusions

It appears that it is possible to use CSD magnitude and the phase of peak alpha activity prior to a seemingly unpredictable upcoming motor response to predict the type of that motor response, at least when possible responses are binary. Further, this predictive ability was best for data obtained 550 ms prior to the stimulus presentation that induced a pre-planned response linked to the stimulus, which is in the time frame associated with type I readiness potentials, the type that occur with some preplanning of future motor movements (i.e., starting at about 1050 ms prior to initiation of the motor movement; [14]). The left frontal (contralateral to the motor response) and midline-to-right-parietal involvement indicated in the critical electrode plots (Fig. 4) is within the boundaries of what might be expected based on previous examinations of type I readiness potentials [14–16], In addition, it may be a coincidence, but the average response time across participants was about 550 ms following the stimulus, suggesting a compelling form of time symmetry. To test this idea, a fruitful future approach may be to reanalyze the data using a trial-by-trial analysis, in which the dependent variables for each trial are the CSD-trace magnitude and the peak alpha phase exactly X ms prior to the stimulus presentation, where X = response time for that trial.

Three important flaws with this study must be highlighted. First, the random selection of the upcoming trial type should be performed following the pre-stimulus period. Although the software did not act on this selection in any way except to store the trial type in the computer's memory, if there is some way in which the participant could sense the presence of this selection remotely then it is difficult to interpret the results as reflecting a precognitive process. Second, these results were obtained with an exploratory step in which the dependent variables were selected, so it is crucial that they are replicated independently prior to drawing firm conclusions. Third, the results were obtained with a pseudorandom number generator, which does not mimic real-life uncertainty, so if a closed-loop system used to predict future events were to be created, it should be based off of data obtained with a truly random (quantum) number generator.

If these results are replicated independently using a random selection using a truly random number generator following the pre-stimulus period, two compelling conclusions can be explored. These are: (1) brain activity may predict motor responses that are, by ordinary means, unpredictable, and (2) type I readiness potentials (and potentially the alpha phase effects observed by Matthewson and others [17]) may be redundant with predictive anticipatory activity, or PAA.

In terms of the implications for creating a closed-loop system based on human physiology, I have several recommendations that arise from the results of this experiment as well as others; some of these recommendations were previously mentioned in an earlier review of PAA [6].

(1) Interindividual differences make the search for a single stereotyped signal difficult; one solution is to use machine learning to better isolate the predictive signal for a given event for each individual.
(2) The complexity of the nervous system may allow for better isolation of signals tied to an array of different future events as compared to a simple binary comparison.

(3) On the other hand, the quick-responding nature of the nervous system, assuming this quick response applies also to the "reverse" temporal direction, is likely to be poorly suited to predict events for purposes that would require seconds to minutes of preparations. In contrast, implicit behavioral effects, like those investigated in the precognition meta-analysis already discussed [7], are among the slowest effects. Thus, if temporal symmetry around an event is a general rule, it is likely that these implicit behavioral measures will also reveal the upcoming event earlier in time than other measures, because they respond later than other measures.

In sum, the results, if replicated independently, support converging evidence that there is some mechanism by which events in time are mirrored by behavioral and physiological systems. Whether these events in time are motor responses (as in this study) or sensory stimuli (as in many others, as machine learning techniques improve, it may be possible to create a closed-loop system able to predict events that previously were thought to be unpredictable. Note that one common concern that impedes the development of such a device is that it would cause a temporal paradox – for instance, the so-called "grandfather paradox" in which an anti-hero can go back in time and kill her own grandfather at a stage in life prior to when her own mother was conceived, thereby making our anti-hero cease to exist. One way to avoid this paradox is to assume that events in time are conditioned according to both information from the past and the future – in other words, what is happening in the present is only possible because past and future events agree with it. An interpretation of quantum mechanics sympathetic with this view has been advanced recently [20], and a formulation of closed timelike curves has been tested to show that it solves for the grandfather paradox using a similar idea [21]. If we can successfully build a closed-loop system that allows people to avoid future dangers, then we will also be better positioned to understand why the system worked. The mechanisms underlying precognition, while still unknown, may well become better understood as we attempt to create such a system.

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