Visual Causality Judgments Correlate with the Phase of Alpha Oscillations

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Abstract

■ The detection of causality is essential for our understanding of whether distinct events relate. A central requirement for the sensation of causality is temporal contiguity: As the interval between events increases, causality ratings decrease; for intervals longer than approximately 100 msec, the events start to appear independent. It has been suggested that this effect might be due to perception relying on discrete processing. According to this view, two events may be judged as sequential or simultaneous depending on their temporal relationship within a discrete neuronal process. To assess if alpha oscillations underlie this discrete neuronal process, we investigated how these oscillations modulate the judgment of causality. We used the classic launching effect with concurrent recording of EEG signal. In each trial, a disk moved horizontally toward a second disk at the center of the screen and stopped when they touched each other. After a delay that varied between 0 and 400 msec after contact, the right disk began to move. Participants were instructed to judge whether or not they had a feeling that the first disk caused the movement of the second disk. We found that frontocentral alpha phase significantly biased causality estimates. Moreover, we found that alpha phase was concentrated around different angles for trials in which participants judged events as causally related versus not causally related. We conclude that alpha phase plays a key role in biasing causality judgments. ■

INTRODUCTION

The ability to perceive and estimate causal relations is essential to help us understand if events relate to each other (Hume, 1739/1967; Michotte, 1963). The interest in identifying the factors that lead us to assume that one event is causing another can be traced back to philosopher David Hume (Hume, 1739/1967). These factors include contingency (i.e., constant covariation), spatial proximity, and, most importantly for this study, temporal contiguity. According to the principle of temporal contiguity, when two events occur close in time, there is a high chance that these are judged to be causally related.[1]

In experimental psychology, the role of temporal contiguity in judgments of causality has been studied using the "launching effect," a display in which an object (e.g., a disk) moves at a constant speed and stops when it touches a second object (Michotte, 1963). If the second object starts to move immediately, observers normally report that the first object caused the second to move. As the interval between the stop of the first object and the start of the second increases, causality ratings decrease; for gap intervals longer than approximately 100 msec, the events start to appear independent (Guski & Troje, 2003; Shallice, 1964; Gruber, Fink, & Damm, 1957).

Intervals of similar magnitude (~100 msec) were also found to be critical in other perceptual phenomena, such as the judgment of stimuli as sequential or simultaneous, masking, and apparent motion (for a review, see Harter, 1967). One explanation for these effects is that perception relies on discrete processing (VanRullen & Koch, 2003). Given the empirical findings, it has been proposed that each distinct perceptual "frame" spans about 100 msec. Growing evidence from electrophysiological recordings suggests that the discreteness of perception might be associated to oscillatory processes in the brain. Several studies have shown that the phase of oscillations in the alpha band (8–12 Hz) is related to several perceptual processes (Jaegle & Ro, 2014; Spaak, de Lange, & Jensen, 2014; De Graaf et al., 2013; Chakravarthi & VanRullen, 2012; Romei, Gross, & Thut, 2012; Dugué, Marque, & VanRullen, 2011; Haegens, Nácher, Luna, Romo, & Jensen, 2011; Busch, Dubois, & VanRullen, 2009). Also, given that the period of this oscillation is of 100 msec, it might be the neural basis of discrete perception (VanRullen & Koch, 2003; Harter, 1967). Although these studies indicate that alpha phase can modulate perception, a much smaller number of experiments have been able to show that it can modulate the perception of stimuli being perceived as simultaneous or sequential (Gho & Varela, 1988; Varela, Toro, John, & Schwartz, 1981). Nevertheless, documenting a direct relation between ongoing phase and temporal framing is essential to empirically support the discrete nature of neural perceptual processing.

Here, we combined the classic "launching effect" with electrophysiological recordings to investigate how the

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phase of EEG oscillations biases causality judgments. Our results show that alpha phase correlates with the perception of causality between two events, which supports the idea that alpha phase can account for discrete perception.

METHODS

Participants

Twenty participants (aged 19–33, eight women, all right-handed) gave informed consent to take part in the experiment. All experimental methods were approved by the Research Ethics Committee at Federal University of ABC. The data from three participants were excluded because of a large number of EEG artifacts.

Stimuli and Procedures

The stimuli were presented using the Psychtoolbox v.3.0 package for Matlab (Brainard, 1997) on a 17-in. CRT monitor with a vertical refresh rate of 60 Hz, placed 50 cm in front of the participant. Each trial started with the presentation of two disks (diameter 0.7°) and a fixation point. After an interval of 800 msec, the left disk moved toward the right disk at a rate of 12°/sec and stopped when they touched (1250 msec after movement initiation); after a delay that varied between 0 and 400 msec, the right disk began to move and halted after 600 msec (Figure 1A). Participants were instructed to judge, at the end of each trial, whether or not the first disk caused the movement of the second disk by pressing one of two designated keys on a keypad.

The delay in each trial was adjusted by two one-up/one-down interleaved running staircases procedures. One staircase started with a long delay (400 msec), whereas the other started with no delay (0 msec). The order of the staircases was randomized (Figure 1B). The steps of the staircase were 67 msec in the first block, 33 msec in the second block, and 16.7 msec in the last four blocks. During the experimental block, after every eight trials, two animations with delays of 0 and 400 msec were presented to remind participants of the extreme delays. Participants were not informed about this and responded normally to these presentations. Each volunteer performed six blocks of 64 trials, totalizing 384 trials. Because of the staircase procedure, the majority of these trials were at intervals close to each participant's threshold.

Psychometric Fitting

The psychometric data from each participant were fitted with sigmoidal logistic functions implemented in the Palamedes toolbox (Prins & Kingdom, 2009). Parameters were estimated separately for each participant. A predicted delay corresponding to a proportion of 50% noncausal response defined the causality threshold (CT; Figure 1C). The comparison between predicted and observed proportions of noncausal responses accuracies yielded a goodness of fit for each participant (mean R^2 = 0.90, lowest = 0.65).

EEG Recording and Preprocessing

Continuous recording from 32 ActiCap electrodes (Brain Products, München, Germany) at 1000 Hz referenced to

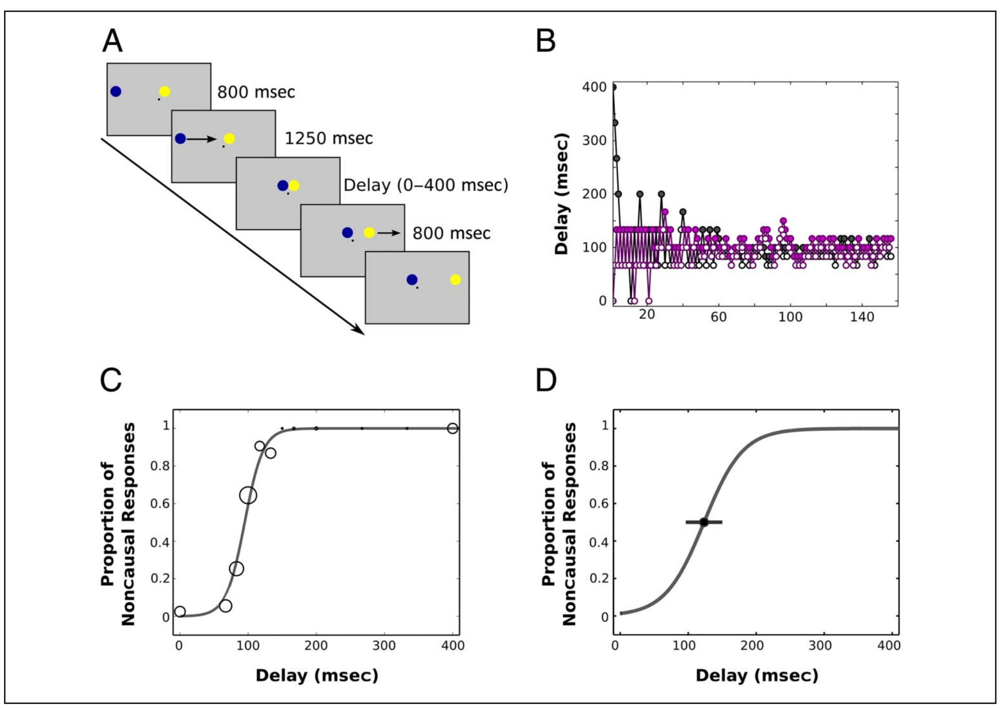

Figure 1. Task structure and behavioral results. (A) Schematic representation of an experimental trial. (B) Staircases and responses of a representative participant. Filled and empty circles indicate noncausal and causal responses, respectively. (C) Proportion of noncausal responses as a function of delay between the events for the same participant. Circle sizes are proportional to the number of trials in each delay. The continuous line shows the fitted logistic function. (D) Fitted logistic function for all participants (n = 17). The circle represents the mean ± *SEM* of the CT.

FCz (AFz ground) provided the EEG signal. The electrodes were positioned according to the International 10–20 system and recorded using a QuickAmp amplifier (Brain Products). Additional bipolar electrodes registered the EOG.

EEG preprocessing was carried out using BrainVision Analyzer (Brain Products). Data were downsampled to 250 Hz and re-referenced to the averaged earlobes. To remove eye movement artifacts, filtered data (0.5–30 Hz) were subjected to independent component analysis and the resulting component coefficients applied to the unfiltered data. Eye-related components were identified through comparison of individual components with EOG channels and through visual inspection. Finally, visual reinspection of single epochs ensured that no artifact remained. A small number of trials were rejected (an average of 2% trials across participants, maximum of 14%), resulting in an average of 375 ± 3 trials per participant (mean ± *SEM*).

EEG Analysis

Time–frequency analyses were done with functions from the Fieldtrip toolbox in Matlab. In a first step, phase and power were computed by means of a continuous wavelet transform of single-trial data for the frequency range from 2 to 20 Hz. The length of the wavelets increased linearly from two cycles at 2 Hz to eight cycles at 20 Hz.

To measure how phases were distributed across trials, we calculated the intertrial coherence (ITC) for each frequency and time point (Lachaux, Rodriguez, Martinerie, & Varela, 1999; Tallon-Baudry, Bertrand, Delpuech, & Pernier, 1996). The ITCs, calculated separately for each participant and electrode, were averaged across the electrodes of interest. To assess the statistical significance of ITCs at the group level, we compared the obtained values with the theoretical distribution of mean resultant vectors given the number of observations using a Kolmogorov–Smirnov one-sample test (as suggested in Batschelet, 1981). This test was applied to each time point and frequency and compared to the values of a similar test performed on surrogate data created by shifting the time course in each trial by a random amount, repeated 1000 times. Finally, to evaluate the statistical difference of the observed ITCs, we performed a nonparametric cluster analysis comparing the Kolmogorov–Smirnov statistics of the original data with those obtained in the surrogate data (Maris & Oostenveld, 2007).

Next, we analyzed how alpha phase biased causality judgments. Individual alpha frequency bands (8–12 Hz) were extracted using third-order Butterworth filters, and the phase and power of these narrow-band signals were extracted using the Hilbert transform. To explore whether alpha phase was correlated with causality judgments, we measured the correlation between alpha phase and CT using an approach similar to the methods used in previous studies, detailed below (Cravo, Rohenkohl, Wyart, & Nobre, 2013; Wyart, de Gardelle, Scholl, & Summerfield, 2012).

RESULTS

Behavioral Results

The mean CT across participants was 123 ± 13 msec (mean ± *SEM*), similar to previous findings (Michotte, 1963).

Alpha Phase Biases Causality Judgments

First, we investigated whether brain oscillations of different frequencies presented a nonuniform phase distribution across trials in the period before the contact of the moving object with the initially stationary target (Figure 2). There were two significant clusters of nonuniform phase distributions on frontocentral sites (Fz/Cz/F3/F4/FC1/FC2). A large cluster (peak $k_{17} = 0.9$, cluster-level $p < .001$) broadly distributed over several frequencies appeared close to the start of the movement of the first disk, which is characteristic of an evoked phase reset.

Interestingly, there was a second, frequency-specific cluster at about 8–12 Hz at the time period near the contact of the stimuli, which also presented a significant nonuniform distribution around its mean phase (peak $k_{17} = 0.47$, cluster-level $p < .001$).

Given that this second cluster was at alpha frequencies and that its scalp distribution was similar to previous results showing effects of alpha phase on performance (Chakravarthi & VanRullen, 2012; VanRullen, Busch, Drewes, & Dubois, 2011; Busch & VanRullen, 2010), we investigated whether alpha phase at these sites at the moment of the second event modulated causality judgments.

For each participant and electrode of interest, alpha phase (8–12 Hz extracted using the Hilbert transform at the moment in which the second disk started moving) was separated into 36 successive but partly overlapping bins—the width of each bin varied so that each bin contained 25% of all trials. For each bin corresponding to a particular alpha phase range, the proportion of noncausal responses as a function of delay was calculated, and performance was measured by fitting sigmoidal logistic functions. As in the behavioral data, CT was defined as the predicted delay corresponding to an equal proportion of causal and noncausal responses.

Because the exact phase at which CT was largest varied between participants, we adjusted each participant's phase distribution. To apply this adjustment, we first estimated the phase for each participant and electrode where the CT was longest. Given that phase is a circular variable, we performed a circular–linear regression of CT with the sine and cosine of alpha phase and calculated

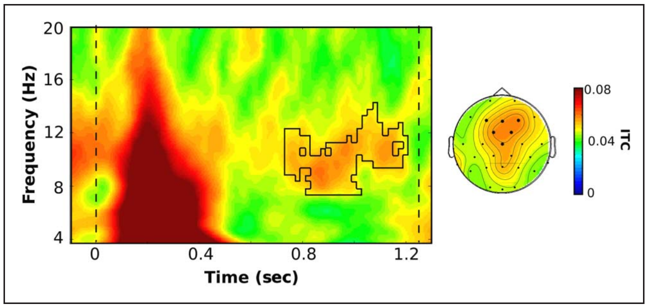

Figure 2. Alpha oscillations are concentrated around its mean phase across trials. Average ITC at frontocentral (Fz/Cz/F3/F4/FC1/FC2) electrodes. The contours indicate the cluster where ITC of endogenous alpha oscillations was significantly higher than chance levels. Dashed lines indicate the start of the trial (0 sec) and the moment of contact of the discs (1.250 sec).

the corresponding preferred phase as the arctangent of the ratio of sine and cosine coefficients:

$$Y = \beta_0 + \beta_1 . \sin(\varphi) + \beta_2 . \cos(\varphi)$$

$$\varphi_{\text{pref}} = \arctan(\beta_1/\beta_2)$$

The phases were shifted such that, for each participant and electrode, the phase at which CT was longest was aligned to a phase angle of zero. The realigned CT was averaged across electrodes for each participant. To minimize the impact of individual variations, the average CT for each participant was subtracted from the binned CTs providing a normalized CT, used in subsequent analyses. At the group level, data from all participants were pooled and a regression was used as previously described. Notice that, because of the realignment, the sine component of the regression is no longer necessary. Therefore, at the group level, a new regression was performed as

$$Y = \beta_0 + \beta_1 . \cos\left(\varphi_{\text{realigned}}\right)$$

To determine the statistical significance of the estimated coefficients, we used the *t* statistic of the regression coefficients and compared the values to those obtained by means of a bootstrap approach. This was particularly important because the realignment of phases for each participant could inflate the values of the estimated coefficients. In each iteration of the bootstrap, we shuffled the CT values across phase estimates for each participant. The randomized CTs were also averaged across electrodes and subjected to a circular–linear regression as previously described. As shown in Figure 3A, alpha phase significantly correlated with the CTs measured in the experiment, with CTs ranging from approximately 110 to 130 msec ($t(16) = 24.67$, bootstrap-$p < .001$; Figure 3B).

We further examined whether this same alpha phase could account for the variance of causal versus noncausal responses not explained by the delay between events. As mentioned previously, behavioral data from each participant were originally fitted with a logistic function. We performed a similar analysis, but now the residuals were stored for each participant. The residuals were then sorted for each electrode of interest according to the alpha phase at the moment in which the second disk started moving. Alpha phases were then classified into 36 successive but partly overlapping bins; the mean of residuals within each bin was calculated for each electrode and participant. Once again, the phase at which residuals were higher varied among participants. We used the same phase alignment as in the analysis of phase and

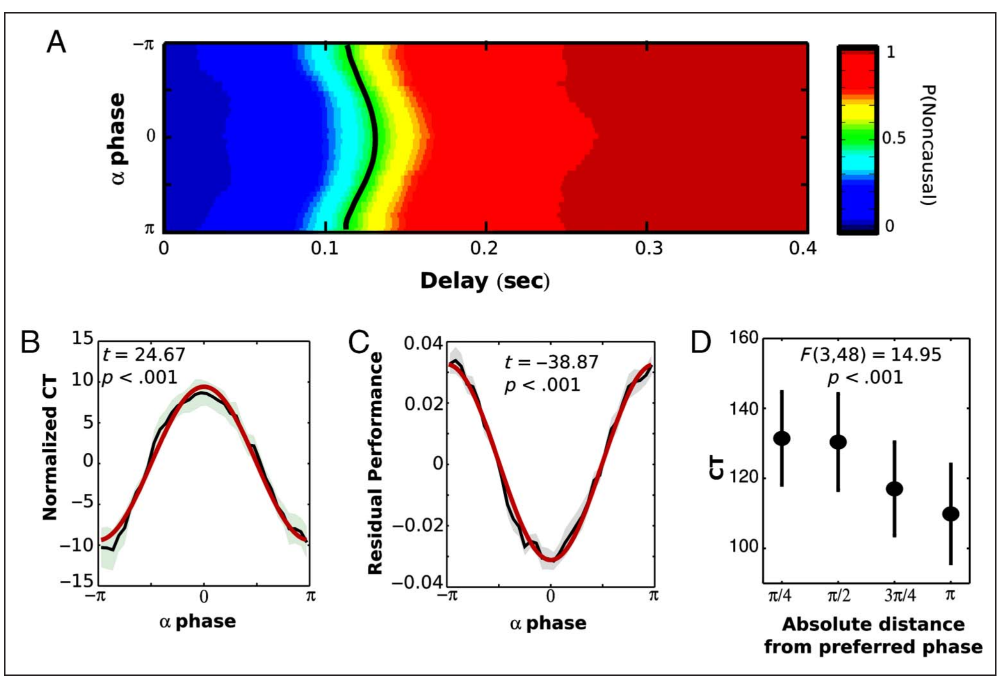

Figure 3. Alpha phase modulates perception of causality. (A) Color map showing the fitted proportion of noncausal responses as a function of delay between events for different alpha phases. Notice how the green area (where there is maximum uncertainty) changes as a function of alpha phase. The black continuous line represents the mean CT for each alpha phase. (B) Normalized CTs as a function of alpha phase. Shaded error bars indicate *SEM*. The red sinusoid indicates the best fit. (C) Residuals of the behavioral fit as a function of alpha phase. Same conventions as previous panel. (D) CTs (mean ± *SEM*) as a function of distance from preferred alpha phase.

CT to verify whether the phase yielding the longest CT responses was also predictive for residual performance. Data were averaged across electrodes for each participant, and a circular–linear regression was calculated for the aggregated results. To determine the statistical significance of the corresponding *t* values, we used a bootstrap approach as previously described. Residuals were significantly modulated by alpha phase ($t(16) = -38.87$, $p < .001$; Figure 3C), indicating that much of the variability from causal responses not explained by delay can be accounted for by alpha phase at the moment of the second event.

To exclude the possibility that the influence of alpha phase emerges as an artifact because of the overlapping binning, we performed further analyses without the overlap. Alpha phase at the moment of the second event was binned as a function of the absolute distance of the preferred phase. In this case, we used only four bins with no overlap based on the absolute difference between alpha phase and preferred phase: (1) less than $\pi/4$ radians, (2) between $\pi/4$ radians and $\pi/2$, (3) between $\pi/2$ and $3\pi/4$, and (4) larger than $3\pi/4$. For each participant and bin, the proportion of noncausal responses was established as a function of delay, and performance was modeled through logistic functions. As in the previous analyses, CT was defined as the predicted delay for a proportion of 50% noncausal responses (Figure 3D). Fitted CTs were submitted to a repeated-measures ANOVA. Distance from the preferred phase significantly affected CTs ($F(3, 48) = 14.949$, $p < .001$, partial $\eta^2 = .027$).

Next, we focused on the analyses of the conditions closest to the threshold for each participant, in which participants classified events as causal or noncausal in approximately half of the trials. As in previous analyses, responses were sorted for each electrode of interest according to the alpha phase at the moment in which the second disk started moving. Alpha phases were then separated into 36 partly overlapping bins. The mean proportion of responses within each bin was calculated for each electrode and participant. Once again, we used the same phase alignment as in the analysis of phase and CT, and data were averaged across electrodes for each participant. Then, data from all participants were pooled and subjected to a circular–linear regression. Statistical significance of the *t* values was assessed with a bootstrap method, as previously explained. We found a significant correlation between alpha phase and proportion of noncausal responses ($t(16) = -12.48$, $p < .001$; Figure 4A).

We also investigated whether the phases for near-threshold trials were concentrated around different means. We used a nonparametric paired-sample test for angles as detailed in Zar (1999) to compare mean phase in trials near threshold in which participants judged the events as causal to those in which they judged the events as noncausal. There was a significant difference in the angles around which the phases were concentrated for each trial type ($R_{16}' = 1.13$, $p < .05$; Figure 4B).

Although our analyses focused on alpha frequencies because of the significant ITC found within this frequency band, we also investigated whether similar effects occurred in other frequencies. We estimated the *t* values for the regression between phase and CT, as previously described, for each time and frequency (from 2 to 20 Hz) from the same channels of interest. This allowed us to estimate the frequency for which the relation between phase and CT modulation was highest. To estimate the mean and variance of these measures, we used a jackknife procedure, performing the same analyses but removing one participant at a time. We found that correlation was strongest in the alpha band (11.2 ± 3.2 Hz, mean ± *SEM*).

Given that recent studies have found that the phase of alpha oscillations only has an effect on perception when alpha power is also high (Mathewson, Lleras, et al., 2011; Mathewson, Prudhomme, et al., 2011; Mathewson, Gratton, Fabiani, Beck, & Ro, 2009), we examined whether the same was true for alpha phase and causality reports. Figure 5 shows the difference in CT as a function of alpha phase at the start of the second movement for both high and low alpha power trials. A 2 × 2 repeated-measures ANOVA with Phase and Power as factors showed a significant effect of Phase ($F(1, 16) = 25.7$, $p < .001$, partial $\eta^2 = .62$) but no

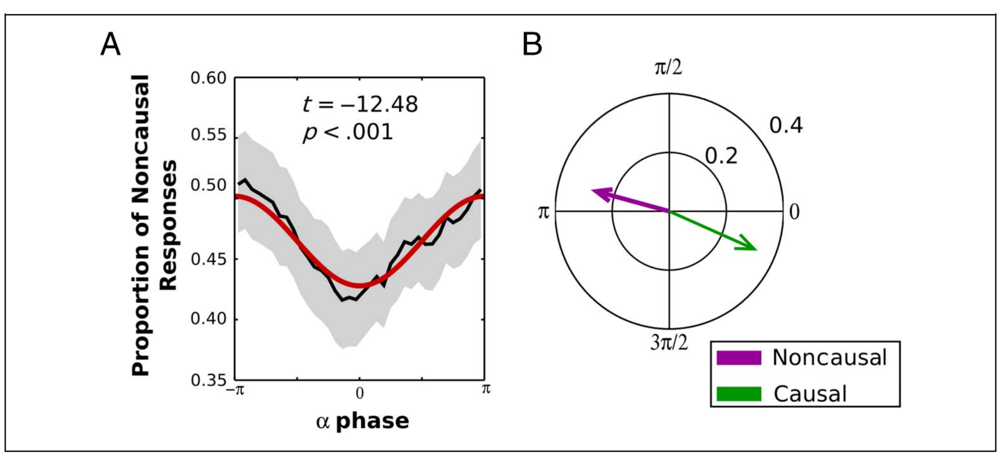

Figure 4. (A) Proportion of noncausal responses as a function of alpha phase in threshold conditions. Shaded error bars indicate *SEM*. The red sinusoid indicates the best fit. (B) Circular plot representing the circular mean and resultant vector length for alpha phase in causal and noncausal judgments in threshold conditions. The length of the arrows indicates the resultant vector length.

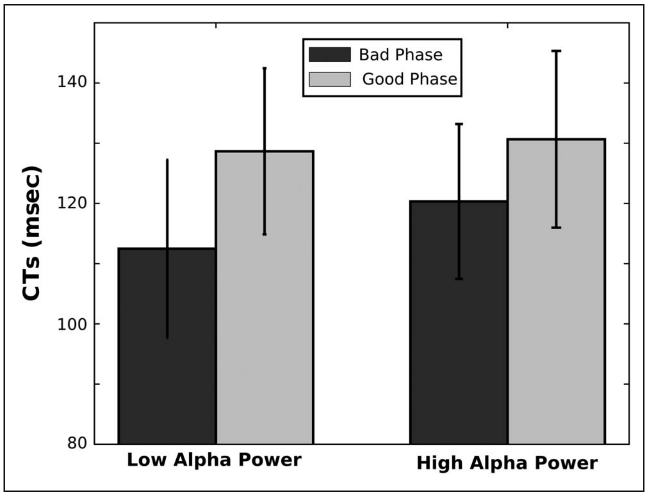

Figure 5. CTs plotted as a function of opposite phases comparing high- and low-power trials. There was a main effect of Phase ($p < .05$), but not of Power or the interaction between factors. Error bars represent *SEM*.

significant effect of Power ($F(1, 16) = 2.34, p > .14$, partial $\eta^2 = .13$), or interaction ($F(1, 16) = 1.35, p > .2$, partial $\eta^2 = .08$).

To investigate whether there was a relationship between CT and individual alpha peak frequency (IAF), we measured the individual peak frequency during the precollision interval in parietal electrodes (P7, P3, Pz, P4, P8) as the frequency with the largest power in the 8–12 Hz range. The average IAF was 9.90 ± 0.21 Hz (mean ± *SEM*). We found no statistically significant correlation between IAF and CT (Pearson correlation: Rho = .08, $p = .74$; Spearman correlation: Rho = .06, $p = .81$). We analyzed the frontal electrodes in the same way and found similar IAFs (9.30 ± 0.21 Hz) with no significant correlation with CT (Pearson correlation: Rho = −.04, $p = .87$; Spearman correlation: Rho = .14, $p = .59$).

DISCUSSION

Our results indicate that the phase of alpha oscillations correlates with causality judgments. One possible interpretation for these results is that they are due to the periodic nature of sensory processes. In fact, a large body of experimental data suggests that this view accommodates several perceptual phenomena (VanRullen & Koch, 2003; Harter, 1967). Growing evidence also indicates that these discrete psychological phenomena can be linked to brain oscillations in the alpha range. Moreover, several studies show that frontocentral alpha phase modulates a number of aspects of perception and action (Hanslmayr, Volberg, Wimber, Dalal, & Greenlee, 2013; Chakravarthi & VanRullen, 2012; Romei et al., 2012; Drewes & VanRullen, 2011; Dugué et al., 2011; Busch & VanRullen, 2010; Busch et al., 2009).

A smaller number of studies, however, have directly addressed the relation between alpha phase and discrete sampling. For instance, Varela and colleagues (1981) presented two successive flashes separated by a fixed ISI of approximately 60 msec. Although at one alpha phase participants judged the two flashes as simultaneous, at the opposite phase they perceived them as sequential (Varela et al., 1981). In a follow-up study, the authors presented these flashes at different alpha phases and different ISIs, allowing for a quantitative assessment of the modulation of the temporal frame by alpha phase (Gho & Varela, 1988). They found that their results were not as consistent and reported a small effect size, but their conclusions were based on data from only three participants. Importantly, they argued that if alpha oscillations modulate temporal framing, then the size of this modulation should be approximately 50 msec, which would be equivalent to half a cycle.

In our study, we show that causality judgments are highly influenced by whether or not the two successive events fall within the same temporal frame. This result is important as it suggests that even judgments not directly associated with sequential/simultaneous judgments can still be modulated by discrete processing. Although we used a larger number of participants than Gho and Varela (1988), the size of the modulation was around 20 msec, still far from 50 msec. However, CTs ranged from approximately 110 to 130 msec, which are within the length of an alpha cycle.

Our results are consistent with the view that alpha phase underlies temporal framing but deviates from the expected size of its modulation. It is important to note that the magnitude of the modulation should be around 50 msec only if the effect size was of half an alpha cycle. Although more intuitive, this view implicitly entails that the alpha cycle is a homogeneous process and that its phase indicates only the point of the cycle at which the event gets processed, without affecting how well it is processed. Nevertheless, several studies have shown that alpha phase biases sensory processing. How might this differential processing affect temporal framing? One hypothesis is to consider the alpha cycle not as merely delimiting a temporal frame but also, through its phase, defining the probability of a certain event being processed in the current or in the next frame. In other words, when presented in "good phases," an event has a large probability of being processed in the current temporal frame. If, on the other hand, the event is presented in a "bad phase," it is probable that it will be processed only in the next phase. This view would be more consistent with current theories about the alpha cycle (Jensen, Bonnefond, & Vanrullen, 2012). Because of the "bad phases," the modulation of temporal framing should be smaller than half a cycle, with its exact size depending on the length of the good and bad phases.

A remaining issue is to determine what might be the mechanism underlying this discrete processing. Our findings add to previous studies that have found similar effects of frontocentral alpha oscillations on several aspects of perception. Given the topography of these results, it is possible that these effects originate in nonsensory associative areas (Wyart & Sergent, 2009). In a recent study using simultaneous EEG-fMRI recordings during a contour integration task, Hanslmayr and colleagues found that the phase of alpha oscillations in a similar frontocentral topography modulated perception (Hanslmayr et al., 2013). Importantly, they also showed that the connectivity across task-relevant neuronal assemblies depended on the phase of these oscillations, suggesting that this oscillatory signal can dynamically control time windows for sensory information transfers between low and high levels of processing. This view is compatible with the notion that different phases within the alpha cycle can modulate whether an event gets processed in the current or in the next temporal frame. When events occur in a bad phase, communication between task-relevant areas might be nonoptimal, causing the event to be processed only in the next cycle.

It is important to note that several attempts to replicate the original findings of temporal framing by alpha phase found by Varela and colleagues have failed (see review by VanRullen et al., 2011; VanRullen & Koch, 2003). Although it is difficult to compare our results with unpublished negative findings, one key difference is that our study was the first one (to our knowledge) that used the launching effect instead of successive abrupt flashes. A significant distinction between these two approaches is that, in the launching effect, participants can anticipate when disks will collide. The significant alpha ITC found before collision might reflect this anticipation. Nevertheless, in our task, the interval between movement onset of the first disk and its touch to the second was 1250 msec, which is an interval that greatly exceeds the alpha period. Thus, the fact that a possible anticipation of the moment of contact was reflected in alpha phase is not trivial and possibly indicates the recruitment of a preferred sampling rate by the visual system. This sampling rate might then be used to try to decide whether or not two events fall within a same temporal frame, giving rise to different causality judgments.

Finally, several recent studies investigated the role of oscillations modulating perception and cognition. These studies suggest that not only the phase of alpha oscillations but also the phase of delta (Cravo et al., 2013; Besle et al., 2011; Lakatos, Karmos, Mehta, Ulbert, & Schroeder, 2008) and theta oscillations (Cravo, Rohenkohl, Wyart, & Nobre, 2011; Lakatos et al., 2009) can modulate perception. Yet, one needs to distinguish experiments examining the role of entrained oscillations from experiments investigating the role of ongoing endogenous oscillations. In several studies, relevant events follow a specific rhythm to which participants can entrain in a bottom–up fashion (Jaegle & Ro, 2014; Spaak et al., 2014; Cravo et al., 2013; De Graaf et al., 2013; Rohenkohl, Cravo, Wyart, & Nobre, 2012; Besle et al., 2011; Mathewson, Prudhomme, et al., 2011; Lakatos et al., 2008, 2009). In these experiments, the phase of the entrained oscillations (as delta, theta, and alpha) is generally found to modulate perception. On the other hand, most studies that investigated the modulation of perception by endogenous oscillations (i.e., when there are no explicit rhythms present in the task structure) found the strongest effects in the alpha band. Although it seems that entrainment can modulate behavior by phase alignment of different frequencies according to the underlying rhythm, there also seems to exist relevant endogenous oscillations (such as alpha) that can modulate perception by means of spontaneous fluctuations. In both cases (entrained and endogenous oscillations), oscillatory phase has been proposed to reflect excitability in local ensembles (Cravo et al., 2013; Mathewson, Prudhomme, et al., 2011; Lakatos et al., 2009). Thus, it seems that even in the absence of an external rhythm to which our brains may entrain, the external environment still gets sampled periodically.

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Note

1. According to Hume, causality is not perceived at all, but presumed causality is inferred from the observation of conjunctions of temporally contiguous events. Although there is a rich and long discussion about whether causality is perceived or inferred, our results do not speak directly to either view. Thus, throughout the article, we will use the more neutral term "causality judgment."

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