Evaluating the Relationship Between Neuropsychological Function and Cognitive Performance

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Abstract

The last 2 decades have produced a vast literature describing relationships between cognitive performance and neuropsychological data. This literature has provided the foundation for countless theories about the neural correlates of cognitive processing and specific theories regarding the role of different cortical areas in human cognition. In this paper, we examine a particular theory – the error likelihood model (Brown & Braver, 2005) – that attempts to account for the function of a particular brain area (the anterior cingulate cortex). A careful evaluation of behavioral data from humans raises questions about the error likelihood model and the implications of neuropsychological data for understanding cognitive performance.

Keywords: Neural Correlates; Anterior Cingulate; Error Likelihood; Cognitive Performance; Change Signal.

Introduction

The last 2 decades have produced a vast literature describing relationships between cognitive performance and neuropsychological data. This literature has provided the foundation for countless theories about the neurological correlates of cognitive processing and specific theories regarding the role of different cortical areas in human cognition. These theories have had a tremendous impact on cognitive science, as well as the perceptions of the general public about the relationship between neural activity and cognitive processing.

The debate surrounding the role and utility of neuropsychological data in understanding human cognition has been ongoing (e.g., Cacioppo, Berntson, Lorig, Norris, Rickett, & Nusbaum, 2003; Coltheart, 2006; Henson, 2006; Uttal, 2001). Whereas evidence of neural correlates have been found in a variety of contexts (e.g., Cabeza & Nyberg, 1997; 2000), direct mappings of information processing activity to particular brain areas may be too simplistic (c.f., Horgan, 1999; Hubbard, 2003; Sohrabi & Brook, 2005). Instead, we argue that it is necessary to understand in detail both the cognitive behavior and the neuropsychological evidence to accurately understand the relationships between neural activity and cognitive processing.

In this paper, we consider a particular example of this complex relationship. We begin with a description of a task – the *change signal task* – which has been used in research attempting to understand the function of the anterior cingulate cortex (ACC) in humans (Brown & Braver, 2005).

Brown and Braver (2005) used fMRI data from participants performing this task to support a model of ACC function they refer to as the *error likelihood model*.

We conducted an extension of Brown and Braver's study using the same task and present the empirical data from human participants here. A detailed analysis of the change signal task and the human performance data provides alternative explanations for most of the human data captured by the error likelihood model, and raises some cautions for those attempting to interpret the significance of neuropsychological data for understanding the underlying cognitive processes of human cognition.

The Change Signal Task

The change signal task is a modification of the stop signal task from Logan and Cowan (1984), which Brown and Braver (2005) used in an fMRI study to examine the function of the ACC in responding to potential errors. In the task, participants are presented with an arrow on each trial, which points either to the left or the right. This is the *go signal.* Critically, on 33% of the trials, a second arrow facing in the opposite direction (the *change signal*) is presented at a carefully controlled delay (the *change signal delay*) relative to the onset of the first arrow. In trials where this arrow appears, participants are instructed to withhold their initial response, and make the response associated with the change signal instead.

The change signal delay is manipulated throughout the task to ensure a relatively constant error rate, however, this characteristic of the task is not revealed to the participants. In Brown and Braver (2005), two stimulus colors were used, and the change signal delay was manipulated independently for each of the color conditions to produce different error rates (error likelihood conditions). In one, the change signal delay tended to be longer, leading to a higher error likelihood, while the other condition tended to have shorter change signal delays with a correspondingly lower error likelihood.

The change signal delay was 250ms in both conditions at the start of the study for all participants. Correct responses led to an increase in the change signal delay; 2ms for the low error likelihood condition, and 50 ms for the high error likelihood condition. In both conditions, errors led to a 50 ms decrease in the change signal delay. These parameters were intended to produce error rates of 4% and 50% in the

low and high error likelihood conditions, respectively. Finally, the change signal delay was constrained to be between 20ms and 800ms, and responses taking longer than 1000ms after the go stimulus presentation were identified as lapses and treated as errors. This last manipulation prevented people from waiting for arbitrarily long periods before making their responses.

Experiment in Brown and Braver (2005)

Brown and Braver (2005) conducted an empirical study to assess the role of the ACC in performing the change signal task. In it, participants completed an average of 535 trials of the task in a single session. While doing the task, fMRI data was collected. Brown and Braver (2005) did not consider in detail the performance data from the study, instead focusing on the fMRI results and their error likelihood model. They did, however, provide supplementary materials that include some additional consideration of the behavioral results.

The change signal task offers interesting challenges for human cognition, and the results presented in Brown and Braver (2005) show that the ACC is sensitive to the differences between go and change trials as well as the error likelihood conditions. Our analysis of the task and data from a replication, however, suggest that many of the findings may reflect artifacts of the task, rather than revealing critical differences in the underlying cognitive processing across conditions by the participants in the study. Before describing this in detail, we provide an overview of Brown and Braver's (2005) error likelihood model, and the relationships between the mechanisms in the model and the fMRI data they presented.

The Error Likelihood Model

The Brown and Braver (2005) error likelihood model presents a theory of ACC function embodied in a neural network-based computational model. The model posits that the ACC functions to detect the likelihood of an error, given a particular task and stimulus context. As they put it, "[the] ACC learns to signal, via the magnitude of its activity, the predicted likelihood of an error occurring in response to a given task condition" (Brown & Braver, 2005, p 1120). They also describe how this conceptualization of ACC function can account for conflict and error detection phenomena that have been shown in ACC activation patterns (e.g., Botvinick, Braver, Barch, Carter, & Cohen, 2001; Cohen, Botvinick, & Carter, 2000).

Brown and Braver suggest that detecting the likelihood of error plays a key role in cognitive control by serving as an "early warning signal" that can be used to recruit resources for performing the task. Thus, a central claim in their theory and model is that ACC activation is used by higher-level cognitive processes to guide adaptive behavior in the task and improve cognitive performance.

The details of the model are beyond the scope of this paper. However, it makes several important predictions in the context of the change signal task. Most intuitively, it predicts that ACC activation should be higher for the high error likelihood condition than for the low error likelihood condition. The authors discuss this effect in their model as a consequence of learned associations between the stimulus color and the likelihood of an error.

In addition to the predicted differences in cortical activation for the error likelihood conditions, the model also predicts differences between *change trials* (where a change signal is presented) and *go trials* (where no change signal is presented), with higher activation for change trials due to the signal these trials provide for reinforcement learning processes in the ACC. The fMRI data from humans show the same qualitative trends, providing support for the model.

A critical finding in support of the error likelihood model was that ACC activation was higher for go trials in the high error likelihood condition than it was for go trials for the low error likelihood condition. It is argued that sensitivity to the stimulus color is responsible for this effect, since these trials are equivalent in all other respects. This is also the primary finding that differentiates the error likelihood model from an alternative account, the response conflict model (Botvinik et al., 2001).

Empirical Study

To better understand human performance in the change signal task, we conducted our own empirical study to obtain detailed data on task performance. In addition to the change signal task, participants performed a two-alternative forced choice (2AFC) task that matched the change signal task, only without any change signals. One motivation for this design was to investigate the role of within task fatigue on changes in response time in the change signal task (see Moore, Gunzelmann, & Brown, 2010).

Methodology

There were 33 participants in the study (18 female and 15 male; ages between 18 and 50). Each participant performed both tasks in a single session lasting approximately 1 hour (task order was counterbalanced). The design of the change signal task replicated the study described in Brown and Braver (2005), except that our participants performed more trials. Specifically, participants completed 6 blocks of 107 trials for a total of 642 trials in our study.

In Brown and Braver's experiment, the association between stimulus color and error likelihood condition was swapped after participants had completed approximately 80% of the trials. This occurred in our experiment at the midway point. Just as in Brown and Braver (2005), this switch in associations between color and error likelihood condition was not signaled to participants. Only one participant in our study reported noticing this manipulation. In fact, only 9 participants were able to accurately articulate the significance of the stimulus colors in the experiment at all.

Results

We collected accuracy and response time data from participants performing the task. Unless noted otherwise, the

results presented here only include data from trials where correct responses were made. Furthermore, the data from two participants were excluded from the analyses because one failed to complete the 2AFC task, and the other exhibited an unusually long string of incorrect responses during the change signal task. As in Brown and Braver (2005), trials where no response was made within 1000ms of the onset of the go stimulus were aborted and treated as errors, with change signal delays adjusted accordingly.

Figure 1 shows median participant response times relative to the presentation of the initial go stimulus across each of the 6 blocks of trials. Firstly, response times for the 2AFC task are stable across all blocks, showing no evidence of within-task fatigue during the course of the experiment, $F(1,19723)=3.144$, $p=.076$.

Beyond the 2AFC, the results for the change signal task are generally consistent with those obtained in the Brown and Braver (2005) experiment, and there are several features that will be relevant for the rest of the analyses and discussion that follows. First, note that the response times for the change signal task are consistently much longer than for the 2AFC, and that there is a wide disparity between the change high and change low conditions. We will demonstrate how these phenomena are related to the dynamics of the task. The closely coupled go low and go high conditions will also be discussed, and it will be shown that participant behavior was indistinguishable between the two.
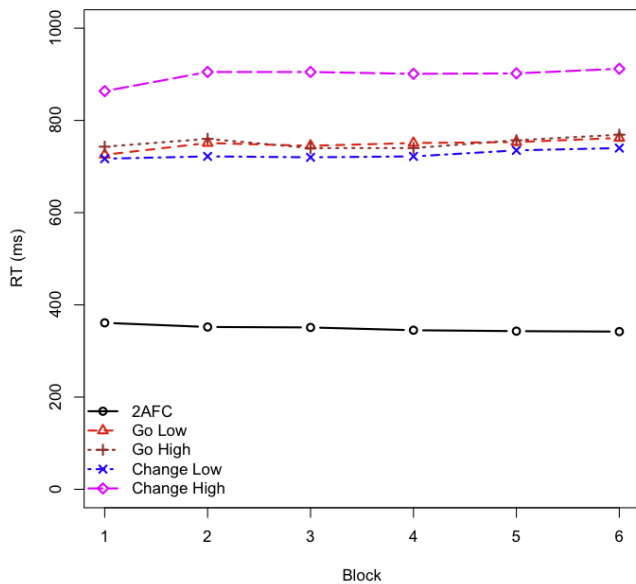

Figure 1: Median reaction times measured from the go signal for the four conditions of the change signal task as well as the 2AFC.

Figure 2 shows a significant ($F_{Low}(1,3180)=444.4$, $p < .001$, $F_{High}(1,1643)=374$, $p < .001$) correlation ($r = .77$) between the change signal delay and the participant reaction time in the change trials. These data illustrate the impact of the change signal delay on overall response times shown in

Figure 1. In fact, if the change signal delay is subtracted from the response times on change trials, the disparity between these conditions nearly disappears (Figure 3).
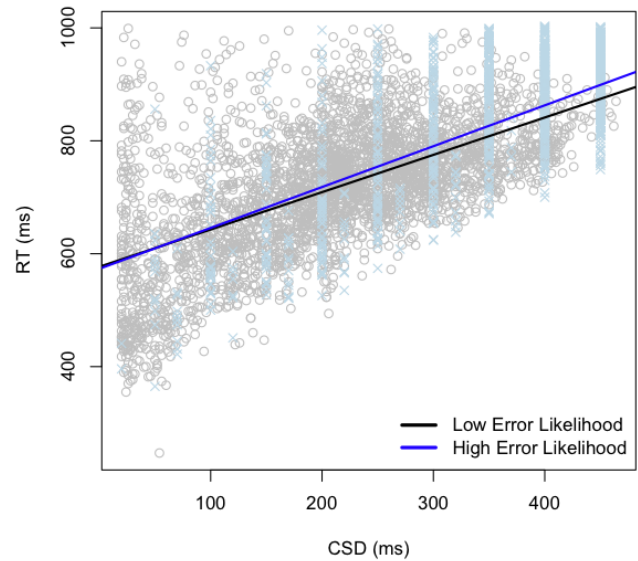

Figure 2: Reaction time as a function of change signal delay in correct change signal trials. Regression lines overlay the lighter scatter plots of each condition.
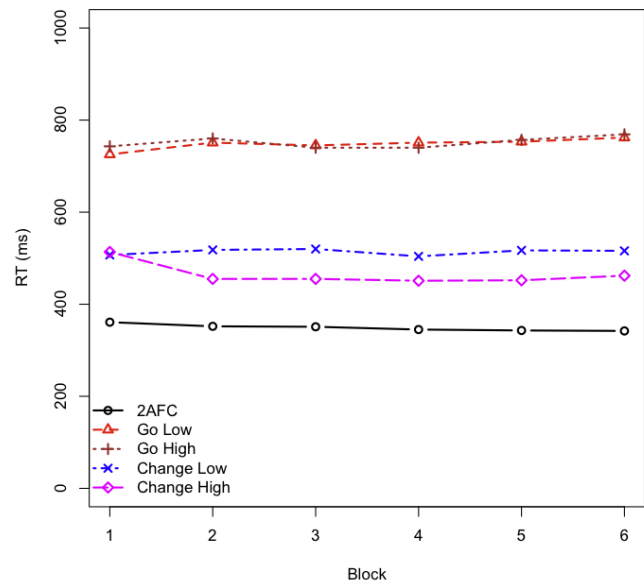

Figure 3: Median reaction times measured from the final stimulus for the four conditions of the change signal task as well as the 2AFC (i.e. the change signal delay has been subtracted from the high error condition reaction times).

One clear consequence of factoring out the change signal delay on change trials is that response times are significantly faster for change trials than for go trials ($t(10836.23)= -17.2995$, $p < .0001$). This effect can be explained in context as a strategic adaptation to the characteristics of the change signal task. Specifically, it is our hypothesis that participants

are intentionally delaying their responses to go signals in hopes of correctly responding to the change signals (Moore, Gunzelmann, & Daigle, 2012).

This perspective accounts for the slower reaction times in the go trials, because it suggests that participants would respond to the go signal only after their strategic delay, or hedge, was complete. It also explains the large difference in response times for the go trials in the change signal task versus response times for the 2AFC task (Figures 1 & 3).

Although we hypothesize that participants also hedge their response in the change conditions, there is no reason for them to delay making a response once a change signal is presented. In change trials, therefore, responses can be initiated as soon as the change signal appears. Moore et al. (2012) present a computational model demonstrating the plausibility of this account.

Another interesting feature in Figure 3 is that median response times for change trials are faster in the high error likelihood condition than in the low error likelihood condition. To understand this average difference, it is necessary to examine the details of human performance in these cases and the characteristics of the task that give rise to the observed results. Figure 4 shows the distribution of response times for the change high and change low conditions (left side), as well as the proportion of lapses in each of the conditions (right side).

Figure 4 illustrates that the difference in response times between the two change conditions in Figure 3 is likely a function of the 1000 ms lapse threshold. In the high error likelihood condition, 15 % of the trials resulted in lapses (see the right half of Figure 4), while only 1% of trials in the low error likelihood condition resulted in lapses. The right side of Figure 4 gives clear evidence that the response time distribution is truncated at the lapse threshold, which has the effect of reducing the median response time for correct responses (lapses are treated as errors).
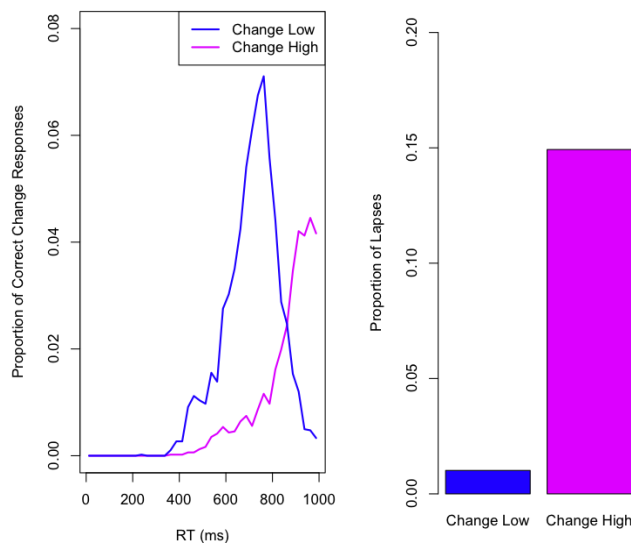
.

Figure 4: Response distribution for the high and low change conditions, and the proportion of lapses for each.

Lastly Figure 5 shows the distributions for the two go conditions. They align extremely well, and Kolmogorov-Smirnov test shows no statistical difference (p=.36). As discussed below, this is an important result, as it generates questions regarding the extent to which people are aware of the significance of the stimulus colors in the task, or the degree to which they are able to use the colors in a meaningful way to adapt to the characteristics and demands of the task. In the next section we compare and contrast the results of our study with the fMRI data described in Brown and Braver (2005).
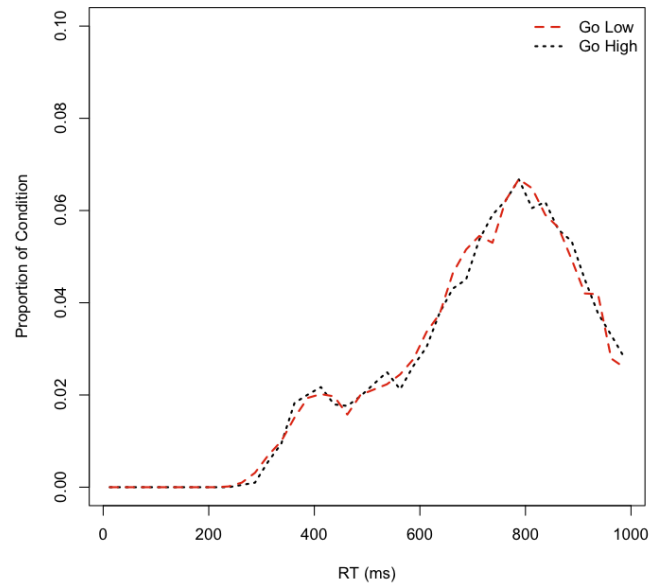

Figure 5: Distribution of response times for go trials in the two error likelihood conditions (accumulated into 25ms bins).

ACC Activation and Error Likelihood

Evidence for the error likelihood model in Brown and Braver (2005) came from fMRI data. However, to fully evaluate the validity and significance of the model, careful analysis of the task and consideration of human performance data are necessary. Based on the analyses of the response time data presented above, we discuss the fMRI findings in this section, showing that nearly all of the critical phenomena in the fMRI data from the task can be accounted for by simply assuming that longer trials (including the change signal delay) lead to more ACC activation (though this may be too simplistic in general; see Mulert, Gallinat, Dorn, Herrmann, & Winterer, 2003; Winterer, Adams, Jones, & Knutson, 2002).

Task Artifacts in Performance and ACC Activation

Brown and Braver (2005) cited several findings in their fMRI data to support the error likelihood model of ACC function. Most of these can be related directly to task-driven differences in response time we found in our study. One

example of this is the finding in Brown and Braver (2005) that activation in the ACC was higher for change trials than for go trials. We did find longer response times for change trials, but the evidence suggests that this difference is an artifact of the task-driven change signal delay (Figure 3).

In addition to the main effect of trial type (change versus go), Brown and Braver (2005) also found greater ACC activation for change trials in the high error likelihood condition than in the low error likelihood condition. Once again, this is associated with a significant difference in response time (Figure 1). The response time difference, in turn, is driven by the difference in the change signal delay between the two conditions. When those delays are factored out of the response times, the difference between those conditions disappears (Figure 3).

The Critical Phenomenon

The only phenomenon that is not captured well by the timing of the presentation of stimuli in the task is the difference in ACC activation between go trials in the two error likelihood conditions that is predicted by the error likelihood model and supported by the fMRI data in Brown and Braver (2005). In this case, the behavioral data diverge from those trends. In fact, our data show essentially equivalent performance, with no significant difference in behavior across conditions (Figure 5).

This result creates an interesting circumstance with regard to assessing the significance of the fMRI data and the implications of the error likelihood model for understanding human cognition. On the one hand, the fMRI data show a significant difference in ACC activation between go trials from the two error likelihood conditions. Importantly, the error likelihood model predicts the fMRI data well, providing a consistent account of neuropsychological data. This is an interesting capacity of the model, and one that adds support to the proposed mechanisms.

On the other hand, while the fMRI data and the model both suggest that the error likelihood conditions are differentiated at a neuropsychological level, there is no evidence that they are differentiated at a behavioral level in our data. Brown and Braver (2005) take the position that the ACC is critical in the recruitment of cognitive control during task performance when the likelihood of making errors is greater. In this case, color provides a cue to differences in difficulty, albeit a cue that is not explicitly described to participants. Importantly, others have failed to replicate the fMRI findings reported by Brown and Braver, even with more explicit cues regarding the error likelihood cues and their significance (Nieuwenhuis, Schweizer, Mars, Botvinick, & Hajcak, 2007).

The critical question is, if the ACC is sensitive to the color of the stimulus as an indication of the likelihood of making an error, why is there no evidence in the behavioral data? The answer to this question is essential to understanding the relationship between cognitive processing and neuropsychological data in the change signal task. We conclude the paper with a discussion of this issue, and more generally the challenges associated with using neuropsychological findings to inform our understanding of cognitive processes.

Conclusions and Implications

Brown and Braver (2005) presented provocative neuropsychological data from a novel task, which they used to validate a computational theory of ACC function. As our results and analyses show, however, questions remain about whether it is task artifacts or cognitive phenomena that are responsible for many trends in the fMRI data, and about the implications of the data and the error likelihood model for understanding human cognitive performance and behavior.

Importantly, the model accounts for what appears to be a critical phenomenon in the empirical study – higher ACC activation for go trials in the high error likelihood condition than in the low error likelihood condition. This is, in fact, the only phenomenon predicted by their model that cannot be explained by the timing of the presentation of stimuli in the task, which directly impacts response times as well. Unfortunately, others have failed to replicate that finding (Nieuwenhuis et al., 2007).

Even if the effect is real, questions remain about what these results mean with regard to the underlying cognitive processes. According to Brown and Braver (2005), the ACC is an "early warning system that recruits cognitive control to match its predicted demand" (p.1120). In the context of the change signal task, however, one would expect that recruiting cognitive control would (1) increase explicit awareness about features in the environment related to error likelihood and/or (2) impact human behavior in a manner consistent with the implications of the likelihood of error.

In support of these expectations, Dehaene et al. (2003) found evidence for elevated ACC activation only in circumstances where stimuli creating conflict in a priming task were "consciously detected" (p. 13726). Based upon our results, however, the manipulation of error likelihood was not obvious to participants, and there was no impact on task performance. This creates some challenges that must be addressed to better understand the cognitive processing involved and the significance of ACC activation in the task.

There is evidence in the change signal task that participants adapt to the change signal delay. As they gain experience with the task, average response times increase, reflecting strategic adaptation to the task. However, there is *no* evidence that their adaptation is sensitive to the distinction between error likelihoods signaled by the two stimulus colors. Instead, reaction times for go trials are virtually identical, regardless of the error likelihood condition (Figure 5). This is also true of change trials, when the change signal delay and truncated response distribution in the high error likelihood condition are taken into account (Figures 3 & 4). An interesting follow-up would be to examine human performance if the role of the colors was explicitly explained to participants before the study began (see Nieuwenhuis et al., 2007 for an experiment along these lines).

Of course, this leaves the incongruity between ACC activation and participant performance in these two conditions begging for a theoretical explanation, in addition to questions regarding the replicability of the phenomena (Nieuwenhuis et al., 2007). Our findings expose the discrepancy and reveal the importance of understanding this finding. And, we hasten to add that our empirical findings do not provide evidence to directly contradict the error likelihood model of Brown and Braver (2005). Taken with the failure to replicate the fMRI findings (Nieuwenhuis et al., 2007), however, there is an indication that further research is warranted to understand human performance on the task and the role of the ACC.

Finally, our results suggest in general that fMRI data, like the results presented in support of the error likelihood model, must be interpreted with caution and considered in the context of the performance of participants as well as the context of the task environment that is the focus of study. We have shown that these factors can add important information to inform theories regarding the relationship of neuropsychological data to cognitive processes. It is only by considering multiple sources of evidence that we will be able to arrive at comprehensive theories of human information processing and cognition and how those functions are realized in the brain.

Acknowledgments

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