Testing fMRI Predictions of a Dual-Task Interference Model

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Abstract

A previously developed ACT-R/threaded cognition model of dual-task interference (Borst, Taatgen & Van Rijn, 2009) was used to predict neuroimaging data in four brain areas. These predictions were tested in an fMRI experiment, which confirmed the predictions in three of the areas. The fourth area, the intraparietal sulcus, showed a different pattern than predicted. To account for this, a new mapping of an ACT-R module onto a brain area was introduced: It was assumed that activation in the intraparietal sulcus not only depends on the problem state module, as is customary, but also on the visual-location module. The resulting model fit well to the human data, confirming the model's assumptions of dual-task interference.

Keywords: fMRI, ACT-R, Problem State, Multitasking.

Introduction

Some tasks can be performed together effortlessly, like drinking coffee and listening to a talk, while other tasks interfere with each other, like talking to a colleague while writing a paper. The challenge for theories of multitasking is to explain why some tasks interfere with each other and some do not. Intuitively this is easy to explain: if tasks use the same cognitive resources they will probably interfere. This idea was formally implemented in the threaded cognition theory (Salvucci & Taatgen, 2008). In threaded cognition, multiple tasks (called 'threads') are active at the same time. Tasks can use several cognitive resources, like declarative memory and the visual system. These resources function in parallel (i.e., the visual resource can be used to perceive an object, while at the same time a fact can be retrieved from memory), but the resources themselves can only proceed in a serial fashion (i.e. the visual resource can only perceive one object at a time). Thus, if multiple tasks need the same resource, one of the tasks will have to wait for the other tasks, resulting in interference.

Salvucci and Taatgen (2008) have shown that, in addition to perceptual and motor resources, two central cognitive resources cause interference in multitasking: declarative and procedural memory. Additionally, we have shown that another central cognitive resource, the problem state, also causes interference in multitasking (Borst & Taatgen, 2007; Borst, Taatgen, & Van Rijn, 2009). The problem state is used to maintain mental representations necessary for performing a task. For instance, when solving '2*x*-7=6' the problem state is used to store the intermediate solution '2*x*=13'. In our previous research, we let participants perform a subtraction and text entry task concurrently. Both tasks were presented in two versions: an easy version in which no problem state was required to perform the task and a hard version in which it was. When both tasks required a problem state, significantly more interference was observed than in all other conditions: response times and error rate increased. To account for these results a cognitive model was developed using threaded cognition and ACT-R (Anderson, 2007).

In the current paper we set out to validate this model using neuroimaging data. First, the previously developed model was used to predict brain activation patterns in four brain regions. Subsequently, these predictions were tested in an fMRI experiment. Before we discuss these points, we will first explain how ACT-R models can be used to predict neuroimaging data.

Using ACT-R to predict the BOLD response

ACT-R (Anderson, 2007) describes human cognition as a set of independent modules that interact through a central production system. For instance, it uses a visual module for perception and a motor module to interact with the world. Besides these peripheral modules, there are several central cognitive modules: the procedural module that implements the central production system, the declarative memory module, the goal module, and the problem state module (sometimes called 'imaginal module'). All modules operate in parallel, but a module in itself can only proceed serially.

ACT-R models are usually tested on a behavioral level: if for instance reaction times and error patterns match the human data, it is concluded that a model gives a plausible account of the observed behavior. However, to find direct evidence for non-observable specifics of models, ACT-R has been extended to predict neuroimaging data (Anderson, 2005). To predict brain activation data, or to be more precise, the Blood Oxygenation Level-Dependent (BOLD) contrast, the modules of ACT-R have been mapped onto small regions in the brain (about 12x12x12mm). The most important modules and associated brain regions for this study are listed in Table 1.

The different modules are not constantly in use during the execution of an ACT-R model, but operate for short periods of time (in the order of hundreds of ms). It is assumed that when a module is active, it will drive a BOLD response in the associated brain region. This response is modeled by a gamma function, as is customary in fMRI research:

$$H(t) = m\left(\frac{t}{s}\right)^{a} e^{-(t/s)}$$

Table 1. ACT-R modules and associated brain regions.

ACT-R Module	*Brain Region*	*MNI Coordinates*
Manual	Precentral gyrus (BA 3)	-37, -28, 51
Visual	Fusiform gyrus (BA 37)	-22, -59, -15
Declarative Memory	Inferior frontal sulcus (BA 45/46)	-42, 22, 21
Problem State	Intraparietal sulcus (BA 7/39/40)	-23, -67, 36

where *m* determines the magnitude of the BOLD curve, *s* the time scale, and *a* the shape. If *D(t)* is a 0-1 demand function that indicates whether a module is active at time *t*, the BOLD function can be calculated by convolving *D(t)* with the gamma function:

$$B(t) = \int_0^t D(x)H(t-x)\mathrm{d}x$$

It should be noted that we do not assume that modules in ACT-R exclusively drive activation in these regions, nor that activation in these regions is only due to the associated ACT-R modules. However, these regions have been the best indicators of activation in the ACT-R modules over a series of studies (see also Anderson, 2007).

Predicting the BOLD response

In this section we will describe how we used the model of Borst et al. (2009) to generate BOLD predictions. We will first describe the task in detail, followed by the model and the predictions.

The task

In the experiment participants had to perform a subtraction and text entry task concurrently (Fig. 1). Both tasks had two versions, an easy version in which participants did not have to maintain a problem state between responses, and a hard version in which they were required to maintain a problem state. Participants had to alternate between the tasks: after entering a number, the subtraction task was disabled, forcing participants to subsequently enter a letter. After entering a letter, the text entry task was disabled and the subtraction task became available again, etc.

In the subtraction task, 6-digit column subtraction problems had to be solved in right-to-left order. In the easy, no problem state version, the upper term was always larger or equal to the lower term; these problems could be solved without 'borrowing'. In contrast, the hard version required participants to borrow 3 times (see Fig. 1). The assumption is that participants used their problem state resource to keep track of whether a 'borrowing' was in progress. Solved columns were masked with #-marks to prevent display-based strategies (i.e. reading previous columns again).

For the text entry task, 6-letter words had to be entered. In the easy version the words were presented one letter at a time. Participants had to click the corresponding button on the keypad, after which the next letter appeared. In the hard version, a word appeared at the start of a trial. When a participant clicked on the first letter, the word disappeared and had to be entered without feedback (participants could neither see the word they were entering, nor how many letters they had entered). It was assumed that participants needed a problem state to keep track of the word and their position within the word ('public, 4th position').

Before each trial, two colored circles were presented on the screen, one on the left and one on the right side, indicating whether the task on that side of the screen was going to be easy (green circle) or hard (red circle). Participants were instructed to act both quickly and accurately. The tasks were performed in all difficulty combinations: easy subtraction/easy text entry, hard/easy, easy/hard, and hard/hard.

Three changes were made with respect to the original task of Borst et al. (2009) to make it suitable for the fMRI scanner: a) letting participants respond using a mouse instead of the keyboard, b) changing the length of the stimuli from 10 to 6 numbers / characters, and c) making the interface more compact to minimize head movement.

The model

We will now describe the ACT-R/threaded cognition model that Borst et al. (2009) developed to account for the task above. Of particular importance for the tasks at hand is ACT-R's problem state module. This module can hold a problem state consisting of one chunk of information, which means that the module's contents have to be replaced frequently when it is required by multiple tasks. A problem state is accessible at no time cost, but replacing a problem state takes 200 ms. If the problem state is replaced, the previous problem state is automatically moved to declarative memory. Thus, the total time to replace a problem state is 200 ms plus the time it takes to retrieve the problem state from memory. Therefore, the problem state resource constitutes a bottleneck in multitasking: switching problem states incurs a considerable time cost.

The two tasks in the experiment were implemented as two threads in the model. Both threads use the visual module to perceive the stimuli and the manual module to operate the mouse and the keyboard. In the easy version of the

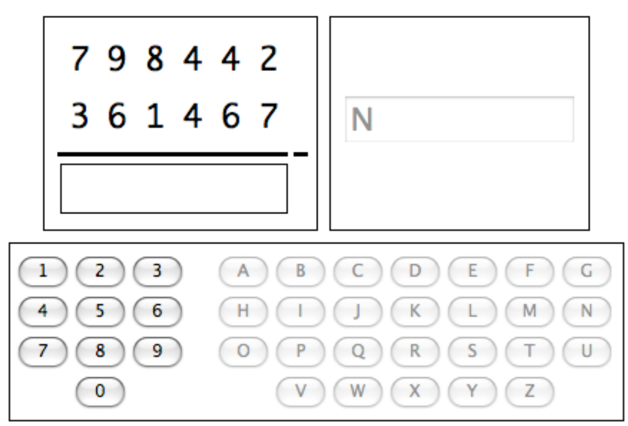

Figure 1. Screenshot of the experiment.

subtraction task, the model perceives the numbers, retrieves a fact from memory (e.g., 5–2=3) and enters the difference. In the hard version the model also starts by retrieving a fact from memory, if its outcome is negative (e.g., 3-6=-3) the model adds 10 to the upper term, stores in its problem state that a ‘borrowing’ is in progress, and retrieves a new fact (13–6=7). If the problem state indicates that a ‘borrowing’ is in progress, the model subtracts 1 from the upper term before the initial retrieval.

In the easy version of the text entry task, the model perceives the letter and clicks on the corresponding button. In the hard version, the model has to recall for each response what the target word is and what the current position is within the word: it uses the problem state resource to store the word and the current position (‘public, 4th position’). If it is in the hard condition, the model does not look at the display, but uses the word and position in its problem state. However, before it can enter a letter, it first has to retrieve an order fact to determine what the next letter is. After entering a letter, the model updates its problem state to reflect that it is one position further in the word.

Because the model only needs multiple problem states in the hard/hard condition, and either zero (easy/easy) or one (easy/hard, hard/easy) in the other conditions, it predicts an over-additive effect of task difficulty on response times and accuracy. Constantly replacing the problem state in the hard/hard condition incurs a time cost, resulting in increased response times; furthermore, incorrect problem states are sometimes retrieved, resulting in errors. This model was used to generate BOLD predictions for the task, which we will describe next.

A priori BOLD predictions

As explained above, the different modules of ACT-R have been mapped onto brain regions. After changing the model to work with the new interface of the experiment (i.e. using the mouse instead of the keyboard), we generated predictions for four predefined regions. For these predictions we set the *a* and *s* parameters in the BOLD equation to 4 and 1.2, respectively. These are customary values in the literature, and as we did not fit our model to the fMRI data but predicted the data beforehand, there was no reason to alter these values. For the same reason the *m*-parameter was not used for scaling, but left at 1. We will discuss the four most important predictions of our model: the manual module, the visual module, the problem state module, and the declarative memory module. The results are displayed in Figure 2; each panel shows the BOLD response over a complete trial (entering 6 letters and numbers).

The predictions for the manual area, part of the precentral gyrus, are displayed in Figure 2A. While in all conditions the same number of responses has to be given, there are clear differences in the model predictions. This is caused by the fact that the individual responses in the more difficult conditions are spaced further apart in time (i.e., response times are higher). Consequently, the BOLD response has more time to decay between each response, resulting in longer but lower activation curves. This is in line with the fact that the area under the curve should be equal in all conditions, as it is proportional to the total time a module is active (Anderson, 2005), which is the same in each condition.

For the visual module a similar pattern can be observed (Fig. 2B). However, here the hard subtraction/easy text entry and the easy subtraction/hard text entry conditions are switched. This is caused by two things: first, when text entry is hard, the model does not have to look at the screen to see what it has to enter, but already knows the word it is entering. Therefore, less visual processing is required in the hard text entry conditions as compared to easy text entry. Second, in the hard subtraction conditions, the model does more visual processing: after noticing that it has to borrow (by reading the upper and lower terms), it reads the upper term again to process the borrowing, and afterwards reads the lower term again to come up with the final response.

Figure 2C shows the predictions for the problem state module. In the easy/easy condition the model does not use any kind of problem state, which accounts for the flat line. In both the easy/hard and the hard/easy conditions an intermediate activity level is predicted as a problem state has to be maintained for one of the tasks. In the hard/hard condition, the problem state has to be replaced on every step in a trial, because both tasks need to maintain a problem state. Thus, we expect much more activation in the hard/hard condition as compared to all other conditions: resulting in an over-additive interaction effect.

A related interaction effect can be observed for the declarative memory module (Fig. 2D). In the easy/easy condition, the model only needs to retrieve simple subtraction facts, which are extremely fast retrievals,

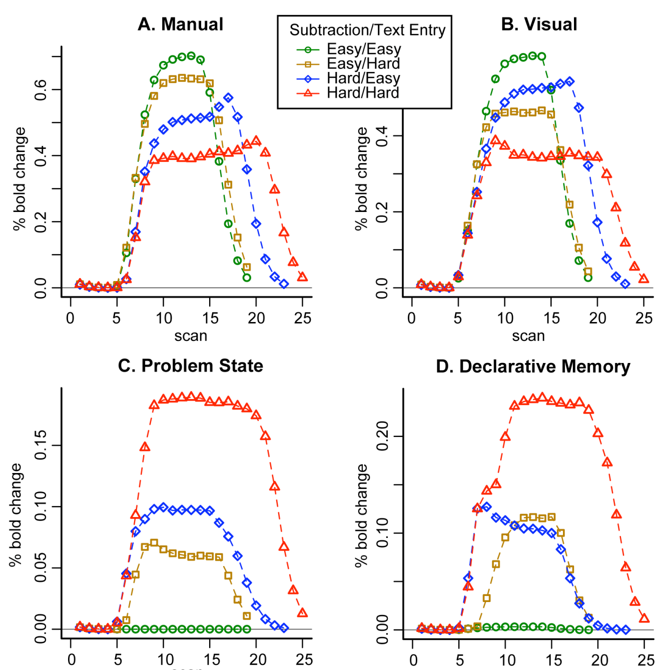

Figure 2. The BOLD predictions. 1 scan is 2 seconds.

resulting in almost no BOLD activity. In the easy subtraction/hard text entry condition, the model needs to retrieve both simple subtraction facts and facts about letter order in words, resulting in higher activation levels. In the hard subtraction/easy text entry condition the model needs to retrieve multiple subtraction facts on most of the steps in a trial, again predicting higher activation levels. In the hard/hard condition there is by far the most activation predicted, as not only the subtraction facts and letter order facts have to be retrieved, but also a problem state on each step.

To summarize, the model predicts *lower* but more persistent activation levels for the harder conditions in the visual and manual modules, and *higher* activation levels for the harder conditions in the problem state and declarative memory modules. We will now describe the fMRI experiment we carried out to test these predictions.

The Experiment

Ten students from Carnegie Mellon University participated in the experiment. Because one of them had abnormal brain anatomy, 9 datasets are left for analysis (2 female, average age 22, range 19-24, right-handed). Informed consent as approved by the Institutional Review Boards at Carnegie Mellon University and the University of Pittsburgh was given before the experiment. Participants received $65.

The 6-digit subtraction problems were generated anew for each participant. In the hard version, each subtraction problem featured 3 columns in which participants had to ‘borrow’, answers were always 6 digits long. The words in the hard text entry condition were handpicked from a list of high frequent 6 letter words (CELEX database) to ensure that similarities between words were kept at a minimum. These stimuli were also used in the easy text entry task, except that the letters within the words were scrambled to create nonsense letter strings, under the constraint that a letter never appeared twice in a row.

Each trial started with the presentation of a fixation cross, followed by two circles indicating the difficulty levels of the tasks, to avoid measuring ‘surprise-reactions’. The circles stayed on the screen for 5 seconds, after which the fixation cross was displayed again for 1 second. Afterwards, the subtraction and text entry tasks were presented. Participants had to start with the subtraction task, after which they had to alternate between the tasks. After entering the last response in each task, a feedback screen was shown for 3 seconds, indicating how many letters / numbers were entered correctly. Between trials there was a 13-17 second break, sampled from a uniform distribution. The start of the circles was aligned to the start of a scan, as was the start of the subtraction and text entry tasks.

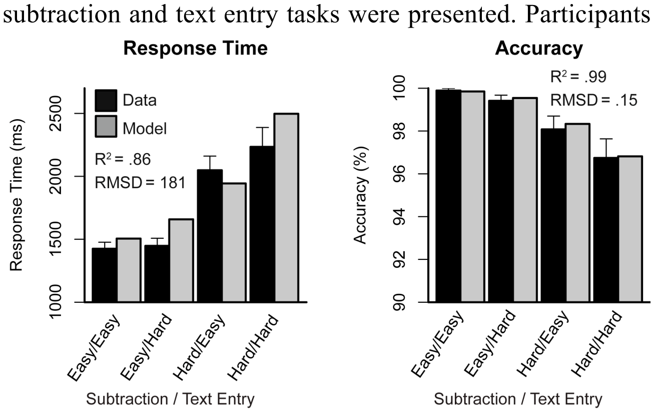

Figure 3. Behavioral results and model predictions.

The experiment consisted of one practice block and six experimental blocks. The practice block was administered during the structural scanning, to familiarize participants with performing the task in the scanner. All blocks consisted of 12 trials, 3 per condition, fully randomized. Thus, the complete experiment consisted of 72 trials. On the day before the scan day, participants practiced the experiment for approximately 30 minutes outside the scanner.

Results

Only the data of the experimental phase were analyzed. Outliers in response times faster than 250 ms and slower than 9000 ms were removed from the data, after which we removed data exceeding 3 standard deviations from the mean per condition per participant (in total, 2.2% of the data was removed). All *F*- and *p*-values are from repeated-measure ANOVAs, all error bars depict standard error.

The left panel of Figure 3 shows the average response time per condition; black bars depict experimental data, grey bars model data. Response times are measured as the time between two mouse-clicks, that is, the time it takes to give a response after having given the previous response. First responses of each task were removed. An ANOVA revealed a significant interaction effect of Subtraction and Text Entry Difficulty ($F(1,8)=6.1$, $p=.04$). A subsequent simple effects analysis showed significant effects of Subtraction Difficulty when text entry was easy ($F(1,8)=12.04$, $p<.01$), and of Subtraction Difficulty when text entry was hard ($F(1,8) = 29.4$, $p<.001$). The simple effects of Text Entry Difficulty did not reach significance. Thus, response times increase with subtraction difficulty, but even more when text entry was hard as well. The right panel of Figure 3 shows the accuracy data. No significant effects were observed, which is probably due to the low statistical power caused by the small number of participants, as such effects were observed in previous studies.

The results are in line with our previous findings (Borst, et al., 2009) and with our hypothesis. However, the effects are slightly smaller than observed previously.

The modeling results are displayed alongside the data in Figure 3. The model predicted an over-additive interaction effect because only one problem state can be maintained at a time. This was indeed observed in the data. However, the model predicted a slightly larger effect, as it was fitted on the data of the previous experiment.

Imaging data: confirmatory analysis

The results in the left precentral gyrus, associated with the manual module, are shown in Figure 4A. The data resemble the model closely: the easier the condition, the higher and broader the BOLD curve. This is explained by the fact that the responses are spaced further apart in the harder conditions, letting the activation decay between responses.

Figure 4B displays the BOLD responses in the fusiform gyrus, associated with the visual module. Again, higher activation levels were found for the easier conditions. The model predicted this, but it also predicted that the hard/easy and easy/hard conditions would switch position as compared to the manual module. While they are closer together, they did not switch completely. Presumably, the participants make less strict eye-movements than our model, and do more visual processing in the hard text entry conditions than predicted.

In Figure 4C the results of the intraparietal sulcus (associated with the problem state module) are shown. As the area under the curves is proportional to the total time a module is engaged (Anderson, 2005), most activation is observed in the hard/hard condition, as the model predicted. However, the model obviously predicted a much larger effect, with a clear interaction effect between conditions.

Finally, Figure 4D shows the activation in an area close to the inferior frontal sulcus, associated with the declarative memory module. Because four of our participants showed a negative BOLD response in the original area, we slightly changed the region to a nearby area where all our participants showed a positive BOLD response. This region, centered at x=-48, y=30, z=30, shows a response that roughly shows the same effects as our model: almost no activation in the easy/easy condition, and an increasing BOLD response with increasing difficulty. However, the effects were not as large as predicted.

To summarize, we confirmed our main predictions that there are higher activation levels in the easier conditions in the visual and manual regions, and that an opposite effect can be observed in the problem state and declarative memory regions. However, the BOLD response in the problem state region was different from the predictions, and the effect in the declarative memory module was less pronounced.

Imaging data: exploratory analysis

Besides the confirmatory analysis, we also performed an exploratory analysis of the fMRI data. The results are shown in Table 2. At the top, regions are shown that were more active in the hard subtraction condition as compared to the easy subtraction condition (uncorrected p-value < 0.001 and contiguous voxel size > 20). First of all, we found a region around the intraparietal sulcus to be active both in the left and the right hemisphere. This region corresponds to the horizontal segment of the intraparietal sulcus (HIPS), which is an important circuit for numeric processing. Next, we found two regions around the right middle frontal gyrus that responded more in the hard subtraction condition than in the easy condition. The more anterior region partly overlaps with ACT-R's declarative memory region. These regions conform to our expectations of more memory retrievals in the harder subtraction condition. The largest active region was found in the medial frontal cortex. It is known that this region is involved in cognitive control and decision making. Not surprisingly, participants need more extensive cognitive control in the hard subtraction condition, as they have to keep track of steps in the borrowing process.

At the bottom of Table 2 regions are shown that are more active in the hard text entry condition as compared to the easy text entry condition (uncorrected p-value < 0.01 and contiguous voxel size > 20). More activation was found in the medial frontal cortex and the intraparietal sulcus; both regions partly overlap with the regions we found for the subtraction task. However, the region in the medial frontal cortex is more posterior and superior, and the parietal region is more central and was only found in the left hemisphere.

Table 2. Results of the exploratory analysis.

Region	*Size in Voxels*	*MNI coordinates (x,y,z)*
Hard Subtraction > Easy Subtraction (p < .001)		
Right Intraparietal Sulcus	102	36, -36, 33
Right Middle Frontal Gyrus	56	39, 36, 24
Medial Frontal Cortex	113	-3, 18, 48
Left Intraparietal Sulcus	41	-45, -42, 39
Right Middle Frontal Gyrus	49	27, 12, 57
Hard Text Entry > Easy Text Entry (p < .01)		
Medial Frontal Cortex	77	-3, 12, 57
Left Intraparietal Sulcus	35	-33, -48, 36

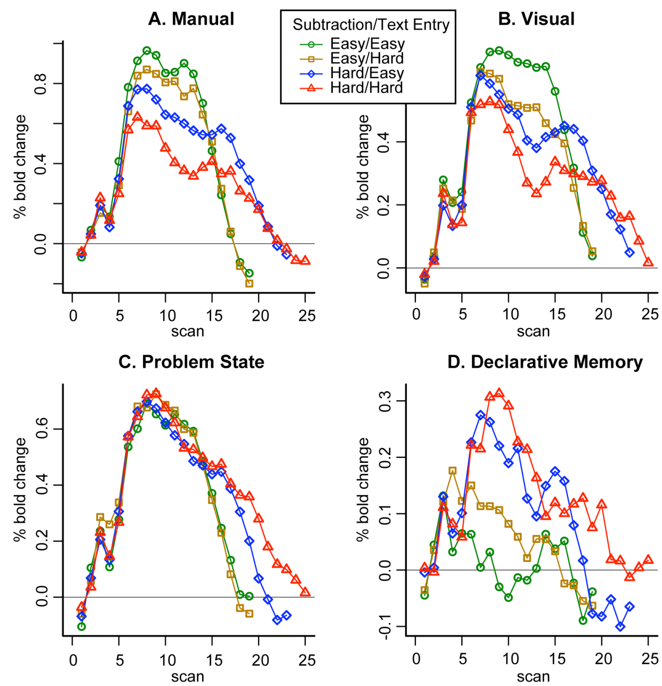

Figure 4. fMRI results for the four regions.

Posteriori Model Fit

One of the predictions of our model was an interaction effect in the posterior parietal cortex. However, instead of clear differences, the data show quite similar curves. While the area under the curves does give an indication of more total activation in the more difficult conditions, the data look very dissimilar from our model predictions.

From previous ACT-R/fMRI research it is known that activation in the problem state region often reflects visual processing (e.g., Kao & Anderson, personal communication; Sohn, et al., 2005), which is consistent with the literature on the posterior parietal cortex (e.g., Culham & Kanwisher, 2001). Figure 5A shows activation in the left fusiform gyrus and the left posterior parietal cortex in the predefined regions of ACT-R during a simple stimulus-response task (Kao & Anderson, personal communication). In this task participants had to press a key in response to the appearance of a stimulus, without any further processing. As can be seen, activation was observed in the posterior parietal cortex. Because in this task no problem states are involved, the activation in the parietal cortex cannot have been caused by problem state activity. On this basis, we argue that activation in ACT-R's parietal region is not only due to problem state related actions, but also to visual-spatial actions. This notion was operationalized by assuming that ACT-R's visual-location module (which represents spatial information and was not mapped onto a brain region before) and the problem state module both cause activation in the posterior parietal cortex.

To let our model make new predictions for the problem state region, we first calculated the influence of the visual system on the posterior parietal cortex in the data of Kao and Anderson. Linear regression showed that activation in the parietal cortex caused by the visual system was best predicted by taking .57 times the BOLD response of the fusiform gyrus. Next, we let the model predict activation in the parietal cortex by adding .57 times the activation of the visual-location module to the activation of the problem state module. The result can be seen in Figure 5B, showing a close fit to the data.

Discussion

In the current study we set out to confirm previous modeling results (Borst, et al., 2009) with an fMRI study. We used an existing experiment and cognitive model of the problem state bottleneck to generate a priori fMRI predictions. These model predictions turned out to be reasonably good indicators of activation in the visual, manual, and declarative memory regions of the brain. It should be noted that we did neither fit the model to the behavioral data, nor fit the model to the fMRI data. Usually, fMRI predictions are fitted to a model by calculating the best fitting *a*, *s*, and *m* parameters, but we thought it more informative to show our a priori predictions using default values.

In the posterior parietal cortex, associated with the problem state module, we found a different pattern than predicted by the model. To account for the BOLD response in the posterior parietal cortex, we let activation in this region depend both on activity of the problem state module, as is customary, and on the visual-location module, which

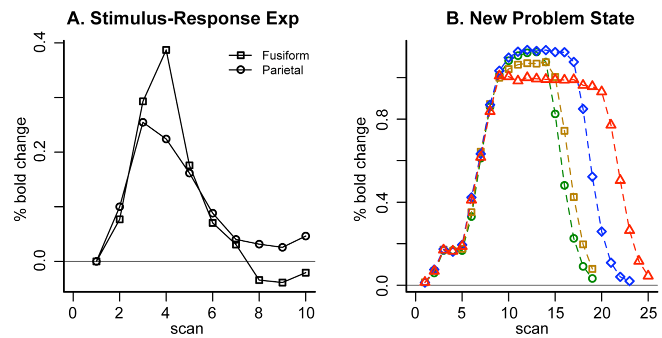

Figure 5. Results of a simple stimulus-response experiment and new problem state predictions.

was not mapped to a brain area before. While it is in accordance with the literature to assume visual-spatial influences in the parietal cortex (e.g., Culham & Kanwisher, 2001), the notion that the visual-location module influences the parietal cortex is tentative, and will have to be confirmed by new studies. Thus, while the resulting model outcome resembles the fMRI data, more experiments will be necessary to confirm the existence of a problem state bottleneck in the brain.

Acknowledgments

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