From fMRI Data To Cognitive Models: Testing the ACT-R Brain Mapping Hypothesis with an Ex-Post Model

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***Abstract*—Recently, John R. Anderson proposed a correspondence between the modules of his cognitive architecture ACT-R and specific brain regions. This Brain Mapping Hypothesis allows the prediction of Blood-Oxygen-Level Dependent curves for these regions using cognitive models. These predictions may be compared to actual data from functional Magnetic Resonance Imaging experiments. While the Brain Mapping Hypothesis has been tested with very simple tasks mostly from algebraic problem solving, we conducted experiments with a more complex task to study the robustness of the Brain Mapping Hypothesis against different domains, multi-dimensional strategy spaces, and modeling errors. The ACT-R model in this paper is a synthesis of our prior models, providing a better fit imaging data. Our results show that the Brain Mapping Hypothesis is not to be dismissed, yet there still remain assumptions in the model that do cause inexact predictions for some modules. We discuss how models of complex problem solvers can achieve a better fit to data by adaptations to their symbolic structure.**

***Keywords*-Cognitive modeling, ACT-R, BOLD prediction, Brain Mapping Hypothesis**

I. Introduction

Cognitive architectures provide a modeling framework with constraints preventing modelers from creating unrealistic models of human cognitive processes [1] [2]. The prominent ACT-R (Atomic Components of Thought-Rational) by John R. Anderson has a long tradition, dating back at least to 1983 [3] [4]. The latest addition to the ACT-R theory is the mapping of its components to brain regions [5], and the enhancement of the architecture with an appropriate tooling to predict Blood Oxygen Level-Dependent (BOLD) responses for these regions.

In Section II, we shall first look into the ACT-R cognitive architecture in general and the Brain Mapping Hypothesis in more detail. We shall summarize our prior related work as well as specify our research question. Section III describes the experiment and fMRI data acquisition and preprocessing procedures. We proceed to the ACT-R model in Section IV. Results are featured in Section V and discussed in Section VI. We finally conclude in Section VII with a summary of this paper and our future directions.

II. State of the Art

The ACT-R cognitive architecture consists of eight modules: The Visual, Aural, Manual, Vocal, Declarative, Imaginal, Goal, and Production modules. Obviously, they perform specific functions: The Visual and Aural modules control the perceptual input channels of an ACT-R model, while the Manual and Vocal modules constitute its action apparatus. The Goal module stores the current goal in the form of control information, while the Imaginal module represents working memory. The Declarative module's purpose is to retrieve facts from long-term memory. All of these modules interface to the Production module via buffers. A buffer may hold a single chunk (i.e., fact) at a time. A chunk contains information in the form of slots, which may either hold atomic data or refer to other chunks in the Declarative memory. The Production module represents the procedural memory and matches, selects, and executes production rules, which compare and manipulate the buffers' contents. All actions triggered by a production in a specific module consume a certain amount of time. Thus, a model based on this architecture is an executable program in the form of production rules and may be used to predict a participant's performance in various tasks on trials of various domains, such as algebraic problem solving.

A. The ACT-R Brain Mapping Hypothesis

Anderson's latest addition to the ACT-R theory, the Brain Mapping Hypothesis, maps the activity of the ACT-R mod-

 ISBN: 978-1-61208-155-7

Table I
CENTERS AND DIMENSIONS OF THE ASSOCIATED BRAIN REGIONS FOR ACT-R MODULES[1]

Module	Region	X	Y	Z	Depth	Width	Height
Procedural	Caudate	±15	9	2	4	4	4
Goal	ACC	±5	10	38	5	3	4
Declarative	Prefrontal	±40	21	21	5	5	4
Imaginal	Parietal	±23	-64	34	5	5	4
Visual	Fusiform	±42	-61	-9	5	5	4
Aural	Auditory	±46	-22	9	5	5	4
Manual	Motor	±41	-20	50	5	5	4
Vocal	Motor	±43	-14	33	5	5	4

ules onto specific brain regions (Table I). Thus, ACT-R implements a tooling that enables BOLD signal predication for these brain regions. However, the regions cover only a very small volume of the brain altogether, and most studies were conducted using simple tasks with a limited strategy space.

Each activity inside an ACT-R module, such as fact retrieval for the Declarative or visual encoding for the Visual module, is recorded along with its duration by the architecture. This trace is used to predict the BOLD response with the following set of functions.

The function $H(t)$ (1) models the hemodynamic response for an active module. It is parameterized by its steepness a, magnitude m, and delay t.

$$H(t) = m(\frac{t}{s})^a e^{-(t/s)} \quad (1)$$

The module's activity trace is captured by the $D(t)$ function at a given time t, which evaluates to either 0 or 1. In combination with the hemodynamic function it accumulated to model the BOLD response (2).

$$B(t) = \int_0^t D(x)H(t-x)dx \quad (2)$$

The postulation of the Brain Mapping Hypothesis has been empirically validated with experiments and cognitive models for various domains, for instance algebra problem solving [6] [7] [8] or associative learning [9].

However, in these experiments the participants were urged to employ a single solving strategy either by instruction or the peculiarities of the experimental design. In contrast to this, our experimental design allowed for the participants to choose their personal strategies during trials.

B. Research Question and Prior Work

Thus, the research question of our project was to study the robustness of the Brain Mapping Hypothesis towards a non-algebraic task, a multidimensional strategy space, and programming or modeling errors. To our knowledge, our research group is, apart from Ragni et al. [10], the only independent research project outside Anderson's lab addressing the Brain Mapping Hypothesis.

Our first-pass models implemented a strategy each and were matched onto functional Magnetic Resonance Imaging (fMRI) data according to behavioral predictor such as response times [11]. With this approach we were able to calculate correlations between modules and regions [12] per strategy. We were not able to dismiss the Brain Mapping Hypothesis [13] and our results finally led to some conclusions for our second-pass model: First, models should use a multitasking approach during the first phase of a trial. Second, subgoals should be set as explicit chunks in the Goal buffer to predict a higher activation.

The model in this paper was implemented ex-post to achieve a better fit to experimental fMRI data. However, we did not touch all but one of ACT-R's internal or BOLD-tools parameters. Rather, we tried to adapt the symbolic structure of the model in order to achieve a better fit.

III. METHODS AND MATERIALS

The particular design of our experiment has been discussed in detail in our previous publications [13]. The task was to determine whether a structural formula matched a chemical compound. The participants in the fMRI study were 62 lower-grade school children ages ranging from 10 to 13. The chemical formula language is usually not known to children of that age group. To prevent carry-over effects in any case, fictional chemical elements and numerals were used. The fMRI experiments were conducted in a multidisciplinary research project, which not only studied the Brain Mapping Hypothesis, but also the impact of affective feedback [14] and the processing of the chemical formula language for school children [15]. The problem may be described as a well-structured rule-using problem [16].

A. Experimental Design

Thus, a trial consisted of the visual and aural presentation of a chemical compound as in Fig. 1. Two structural formula were presented at the left and the right. The participant had to decide which one of these matched the chemical compound. For this, the participant was familiar with the following constraints for the chemical language:

1) The abbreviation for an element is defined by two letters
2) The first letter of the abbreviation is the same as the first letter in the name of the element
3) Both letters appear in the element's name.
4) An element may have a multiplicity from 1 to 4 in the compound. Distinct three letter words served as numerals to denote the multiplicity:
   - 1/-
   - 2/pli
   - 3/pla
   - 4/plo

[1] in Talairach coordinates, voxel size 3.125 mm × 3.125 mm × 3.2 mm

 ISBN: 978-1-61208-155-7

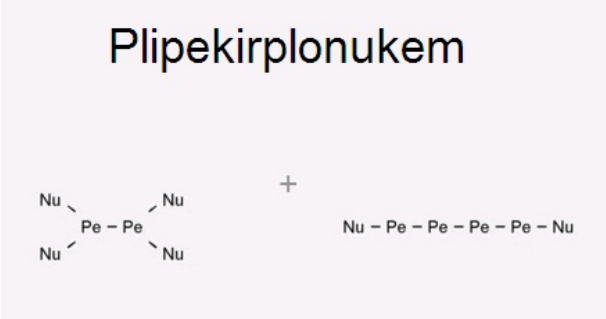

Figure 1. A sample trial [13] where a numeral constraint is violated

5) The position of a numeral is always in front of the owning element in the compound name
6) The central element of the structural formula is always the first in the compound name

The visual presentation of the problem lasted for 4.5 seconds. During this timespan and an additional second the participant could respond, so that the complete trial solving phase lasted for a maximum of 5.5 seconds. After that, a variable jitter time between 2 and 18 seconds followed before feedback presentation, which in turn lasted for 2.5 seconds. Subsequently, another jitter time between 2 and 18 seconds followed before the begin of the next trial.

B. fMRI Data Acquisition

The participants were presented 80 trials in two runs of 40. The fMRI data were acquired using a Siemens MAGNETOM Sonata (1.5 T) system with a standard whole-head coil, obtaining $T2_*$-weighted echo planar images with BOLD contrast (matrix size: 64×64, pixel size: 3×3 mm^2).

Each functional run resulted in 408 volumes of 30 3-mm thick axial slices with a 0.6 mm gap (TR=2s, TE=50ms). Preprocessing was performed with the Statistical Parametric Mapping (SPM5) software. After rigid body motion correction, the time series from each voxel were temporally realigned to the middle slice. Structural and functional volumes were coregistered and spatially normalized to a standard T1 template based on the Montreal Neurological Institute (MNI) reference brain using $2 \times 2 \times 2$ mm^3 voxels. To accommodate inter-subject anatomical variability, the data were smoothed with a Gaussian kernel of 8 mm full-width-half-maximum.

After preprocessing, the fMRI data were analyzed with a Regions of Interest (ROI) approach [17]. The ROIs (see also Table I) were defined by the ACT-R Brain Mapping Hypothesis [5]. Locations and dimensions of the ROIs were transformed from Talairach into MNI coordinates. The raw gray values for all voxels contained by each ROI were averaged, resulting in time series of BOLD responses per participant for each ROI in left and right hemispheres respectively.

IV. Calculation

To find the correct structural formula, the constraints from Section III-A may be checked with the following tasks [13]:

- T1 Visually and/or auditorially perceive and the different parts of the compound name
- T2 Count the outer elements of a structural formula (T2a) and compare them with the second numeral in the compound name (T2b).
- T3 Count the inner elements of a structural formula (T3a) and compare them with the first numeral in the compound name (T3b)
- T4 Compare the inner element with the first element of the compound name
- T5 Compare the outer element with the second element of the compound name
- T6 Indicate the correct formula

Task T1 can be parallelized with T2a and T3a as the compound name is presented auditorially and does not necessarily need the visual input channel. Tasks T2-T5 may be applied to either the left or the right structural formula, or even both. Thus, the most efficient problem solver restricts himself to the evaluation of just one structural formula and decides whether it matches, or, in case a constraint is violated, if it does not.

A. ACT-R Model

Our prior models represented multiple strategies that differed in their sequences of T2 to T5 and formula positions. The model in this paper attempts to reunify these strategies.

Thus, the model may instantiate task sequence. Tasks T1, T2a, and T3a run parallel and share a common chunk in the Goal buffer, as our model validations favored multi-threaded models. Tasks T2a and T3a are always instantiated together and may run for both left and right formula locations.

The productions for Tasks T4 and T5 create separate subgoal chunks in the Goal buffer, thus they run single-threaded and no productions concerning other tasks may fire during their execution. They also regress to the visual presentation of the compound name to check whether the second letter of symbol appears in the elements name.

Each execution of the Tasks T2a/T3a, T4, and T5 creates a chunk in the Imaginal buffer to store the temporary information it needs for its context. Upon task completion this temporary information is translated into control information and transferred into the precedent parent goal.

If a constraint is violated, or all tests for a structural formula have a positive result, productions for T6 may fire and the model indicates the correct formula. If, however, 4.5 seconds have passed and the model is still busy, the model makes a guess and chooses the formula with the greater number of positive tests. It does not give a response if both formulae have the same number of positive tests.

In order to randomize the task execution sequence, the ACT-R parameter `:egs` for expected gain noise had been set

 ISBN: 978-1-61208-155-7

to 0.04. The noise added to the productions' utilities results in random task sequences. This is based on the work of Jones et al. [18], who used this technique to differ between 'adult' and 'children' models, the latter being more explorative in terms of strategies.

For instance, the trial from Fig. 1 could be evaluated with the following three task sequences:

$$S_1 = \{T1, T2a/T3a[Left], T3b[Left], T4[Left], T2b[Left], T5[Left], T6[Left]\} \quad (3)$$

$$S_2 = \{T1, T2a/T3a[Left], T3b[Left], T4[Left], T2a/3a[Right], T3b[Right], T6[Left]\} \quad (4)$$

$$S_3 = \{T1, T2a/T3a[Right], T3b[Right], T6[Left]\} \quad (5)$$

Thus, the first sequence (3) would completely evaluate the left formula and come to the conclusion that it is indeed correct. The second sequence (4) would first evaluate parts of the left formula, then switch over to the right, find the discrepancy in the numerals and indicate the left formula as correct. The third sequence (5) would just evaluate the right formula and find the correct answer sooner than the other sequences. These sequences instantiate different strategies, which differ in their effectiveness for a given trial.

B. Data Analysis

The model makes adequate predictions for trials regarding response times as is shown in Fig. 2. It does not recapture the error rates, i.e., wrong responses and time-outs, correctly. This however, shall be of no concern in this work as we will only study correctly answered trials.

For data aggregation, the time series per ROI and participant for the whole experiment were split into short time series for each trial with a correct response by the participant. As the trials have different lengths, they were aligned onset-locked to a 12-scan template with the method from Carter, Anderson et al. [7]. In contrast to our previous studies, all scans from the trial and feedback phases were included.

After linear detrending, the percentual changes in the BOLD response were calculated and averaged across participant and trials, resulting in a single average BOLD response. Likewise, the model's BOLD predictions were aligned to a template and averaged. As the model can produce different traces for the same trial, this variability was captured by processing predictions from multiple model runs per trial. Both curves, averaged BOLD responses and predictions, were compared using Spearman's rank correlation coefficient for each Module/ROI pair.

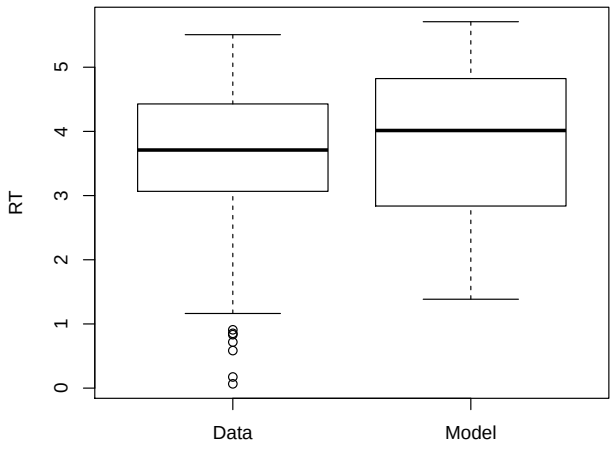

Figure 2. Response times (RT) in seconds for participants and model

V. Results

The correlations in Table II between model and data are high for both regions for all modules but the Manual module, which only correlates with the left hemisphere. The predictions for the Production ROI in Fig. 3(a) fit the data well as in our previous studies, as do those for the Goal module in Fig. 3(b) when compared to our prior results. Apparently, the creation of extra subgoal chunks has raised the magnitude of the predictions. The predictions from the Imaginal module in Fig. 3(d) have a high correlation but do not reach the magnitude of the actual BOLD curves. So do the predictions for the Visual, Aural, and Manual ROIs in Figs. 3(e), 3(f), and 3(g) respectively, but the predictions from the Declarative manual in Fig. 3(c) exceed the actually measured BOLD signal greatly.

The latter observation of over-estimation may be easily explained. The ACT-R model makes heavy use of the Declarative module, by trying to recall previous problem instances of element symbols and names. This strategy is not necessary for solving the problem efficiently and may not be employed by participants. For the other modules except Production and Goal, the model apparently does not exert enough actions on the respective modules to explain data, at least if the ACT-R default value for the magnitude parameter m (Section II-A) is used.

VI. Discussion

From these results, we can deduct some further guidelines for our model. First, we need to create even more extra subgoal chunks, for instance for Tasks T2a/T3a. This should heighten the magnitude of the predictions for the Goal module. However, the low magnitudes for the Visual, Aural, and Manual modules as well as the Imaginal module will not be as easily addressed. Chunk creation in ACT-R is time-costly. Thus, a model exerting many chunk creation actions

 ISBN: 978-1-61208-155-7

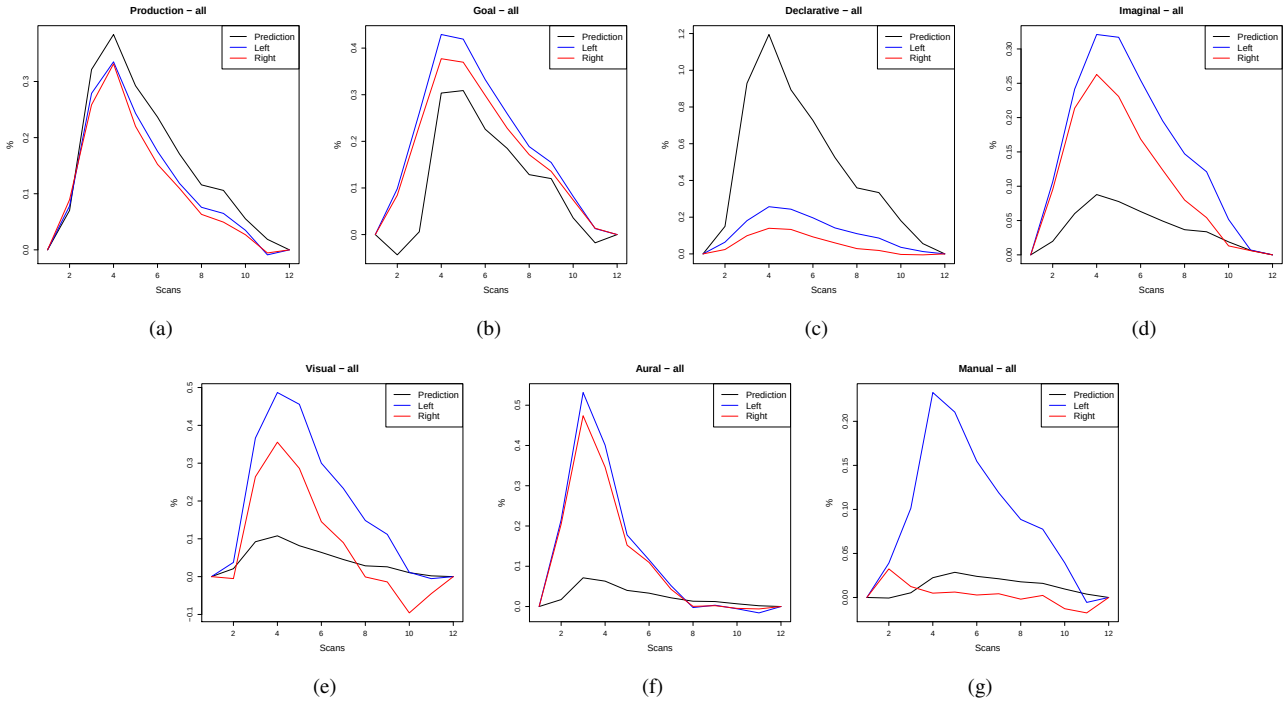

Figure 3. Predicted and actual BOLD curves for regions, averaged across all trials for Production 3(a), Goal 3(b), Declarative 3(c), Imaginal 3(d), Visual 3(e), Aural 3(f), and Manual 3(g) module/region pairs.

Table II
CORRELATION COEFFICIENT ρ FOR LEFT AND RIGHT HEMISPHERES

Module/Region	Left	Right
Production/Caudate	0.958	0.958
Goal/ACC	0.825	0.825
Declarative/Prefrontal	0.972	0.902
Imaginal/Parietal	1.000	0.972
Visual/Fusiform	0.972	0.734
Aural/Auditory	0.832	0.895
Manual/Motor	0.874	0.165

on these buffers would not be able to give a valid response within the maximum response time. We could adjust ACT-R's parameters for the BOLD tools, such as the magnitude parameter m (Section II-A), but since the Production and Goal predictions fit so well this does not seem the right approach. The internal ACT-R parameters for chunk creation latencies seem better suited for our purposes. The model spends too much effort into fact retrieval, thus the next model shall encode more factual knowledge directly in the production rules rather than in declarative memory.

VII. CONCLUSION

We were able to show that the ACT-R Brain Mapping Hypothesis also holds in large parts for tasks with multi-dimensional strategy spaces. However, our prior findings seem once more confirmed. ACT-R is under-constrained: A kind of 'best-practice' manual for ACT-R modeling is missing. Thus, an ACT-R modeler is free to implement many different strategies based on assumption, and some, if not all of these models would explain behavioral data. Still, these ACT-R models do not necessarily explain fMRI data according to the Brain Mapping Hypothesis. We have shown that the only reliable way to achieve a good fit is to adapt the model's structure to the fMRI data itself rather than to base it on behavioral predictors and task decompositions alone.

The ex-post model presented in this paper is able to reproduce a multitude of strategies. It explains fMRI data better than its single-strategy predecessors, yet the activation level is not high enough for some of the regions. From these results, we are able to make educated guesses, which shall guide our next steps and should result in an even more fine-tuned ACT-R model. It will be interesting to check whether the Brain Mapping Hypothesis in combination with this model finally allows to infer the particular task executed by individual participants, using the BOLD curves as predictors. By this, we hope to achieve the identification of Goal states for individual fMRI data. A cognitive model that is able to anticipate internal states for complex problems from neurobiological data could have many applications.

ACKNOWLEDGMENT

The study was supported by a grant from the German Ministry for Education and Research (BMBF Grant No: 01GJ0805). We wish to thank Mrs. P. Arndt, Mrs. B.

Moschner, Mrs. I. Parchmann, Mrs. A. Anschütz, and Mr. S. Bernholt for the experimental design and support by discussing our results.

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 ISBN: 978-1-61208-155-7