Cognitive architectures as a tool for investigating the role of oscillatory power and coherence in cognition

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Abstract
While there is an increasing interest in the role of brain oscillations in cognition, relatively little is known about the mechanistic role of oscillatory synchronization in information processing. Here I highlight a new tool for model-based neuroscience that is particularly well-suited to investigating the role of oscillations in information transmission: cognitive architectures such as ACT-R. ACT-R describes in detail how information is transmitted between its different cognitive resources, and given that oscillatory coherence has been associated with information transfer, ACT-R may be a helpful tool to understand the role of oscillations in the brain. The ACT-R cognitive architecture has been related to functional magnetic resonance imaging activity with great success. Yet, to date there has been very little work in relating ACT-R to electroencephalography (EEG) data. Therefore, my goals are (1) to investigate what oscillatory correlates are associated with the different ACT-R components (cognitive resources), and (2) to assess whether the identified oscillatory correlates exhibit patterns of coherence that would be predictive of their communication. I show that the dynamics of different components of ACT-R are associated with specific patterns of brain oscillations recorded with EEG during an attentional blink task; ACT-R’s working memory resource is primarily associated with parietal 4–9 Hz theta oscillations, while ACT-R’s declarative memory, visual perception and procedural resources together are correlated with posterior theta oscillations. I further show that ACT-R’s predictions about inter-module communication during the processes of stimulus identification and target consolidation are associated with selective increases in coherence at the predicted times.

Keywords: EEG; ACT-R; attentional blink; oscillations; model-based neu-
Introduction

There is a large literature about the role of the brain oscillations that can be observed in EEG in cognition and behavior (Buzsáki, 2006). An important claim is that one of the principal functions of oscillations in EEG activity is providing a way for different parts of the brain to communicate (Varela et al., 2001). Communication is thought to be subserved by increases in synchronization or coherence in EEG activity of pairs of electrodes. Yet, studies ascribing a specific functional role to patterns of synchronization or coherence are quite scarce. An important reason for this gap in the literature is that there are no detailed theories that predict what coherence of a particular set of electrodes at a particular point in time would mean. I will demonstrate that model-based neuroscience (Forstmann et al., 2011) using cognitive architectures could play an important role in filling this gap.

Cognitive architectures are simulatable theories of human cognition that describe multi-step cognitive tasks from input to output. In contrast to mathematical models of cognition that are more conventionally used in model-based neuroscience and that focus on a unique and essential cognitive mechanism for a particular task, cognitive architectures aim to describe (commonalities across) many different cognitive tasks. These architectures therefore aim to describe the functioning of a complete human brain rather than a specific part. One of the cognitive architectures for which the brain-to-model mapping has worked very well is the ACT-R (adaptive control of thought - rational) cognitive architecture (Anderson et al., 2008). This cognitive architecture has been implemented to a wide range of cognitive tasks, including free recall (Anderson et al., 1998), attentional blink (Taatgen et al., 2009), and flying a plane (Gluck, 2010). ACT-R consists of several cognitive resources that work together to produce the desired behaviour. Visual and auditory input is handled by the visual and aural modules, respectively. This input is transformed to output with the help of the declarative memory (retrieval) and working memory (imaginal) modules, guided by a module that keeps track of the current goal. The procedural module organizes the interaction between modules. Output is produced by the manual (or motor) module. Tasks can be implemented in this cognitive architecture by specifying a set of so-called “productions,” which are essentially if-then rules that consist of conditions that should apply to a (combination of) cognitive resources, and
associated actions those resources then perform. As such the architecture’s different modules together simulate the output that a human participant would also produce. Rather than minimizing the number of parameters used to describe a certain cognitive phenomenon, as is done in mathematical psychology, model constraints arise from implementing different cognitive tasks in the same cognitive architecture.

Each of ACT-R’s modules has been associated with neural activity in a specific brain area. The visual and aural modules are associated with fusiform cortex and secondary auditory cortex, respectively. The retrieval module has been associated with lateral inferior prefrontal cortex, while the working memory module has been associated with a subregion of parietal cortex on the border of the intraparietal sulcus. The goal module has been associated with the anterior cingulate cortex, and the procedural module with the basal ganglia. Several experiments have verified this mapping of ACT-R module activation to the brain using functional magnetic resonance imaging (fMRI) activity (e.g., Borst et al., 2010, 2011; Stocco & Anderson, 2008). In addition to clarifying the neural basis of the ACT-R cognitive architecture, this mapping has yielded new insights into brain function, e.g., by demonstrating the neural overlap between different tasks (Borst & Anderson, 2013).

Despite the success of the mapping between ACT-R and the brain through fMRI, there has not been a comparably comprehensive mapping between ACT-R and the brain through electroencephalography (EEG) data. Why would such a mapping be useful? Compared to fMRI, EEG has a much higher temporal resolution (on the order of milliseconds). Although this high temporal resolution of EEG compared to fMRI is offset by its comparatively low spatial resolution, EEG is well-suited to answering questions about differences in the modules’ time courses of activation as well as their interaction. Why is this important? Cognitive models often differ in the time course of activation of various modules, but this may not always lead to observable differences in behaviour (see e.g., Ditterich, 2010). Consequently, it may sometimes be impossible to distinguish different cognitive models on the basis of behaviour alone. Yet, these different cognitive models could potentially still be distinguished by means of neural activity—provided this activity is recorded at a sufficiently high temporal resolution. EEG could provide such temporal resolution. If two models give virtually identical fits to behavioural data, but one model produces time courses that correlate better with EEG activity, then this model may be a more plausible account of
Figure 1: Imaginal module’s failure to activate for the second target causes the attentional blink. This figure shows the activation probability of the imaginal module in four different task conditions: lag 3 (in which targets follow each other relatively closely—being separated by only 2 non-targets) and lag 8 (in which targets are more distant—being separated by 7 non-targets). For targets that follow each other closely in time, the second target tends to be missed (“blinked”). According to the model, this is caused by a failure of the imaginal module to activate for the second target, thereby preventing its consolidation into memory (second row). For targets that do not follow each other closely in time, there are always two activations for the imaginal module (third and fourth row). In that case, the second target is missed due to random fluctuations in attention.

the behaviour under study.

More importantly, ACT-R (or other cognitive architectures) could contribute to our understanding of the function of brain oscillations in cognition. While EEG is usually analyzed in terms of event-related potentials (the average electric field measured in an electrode reflecting the neural response to a certain event), another way is to examine electrical activity in different frequency bands that need to necessarily be time-locked to an event: oscillatory EEG activity. It has been proposed that coherence in such oscillatory activity can be used to communicate and bind information across different parts of the brain (e.g., Singer, 1993). Since ACT-R provides a theory of the information transmission and coordination between its different modules (cognitive resources), I propose it can be used to understand the role of oscillatory coherence in cognition.

Given these promising perspectives, it is perhaps surprising that to date no comprehensive mapping has been made between EEG activity and the
activation of a complete ACT-R model. To date, all that exists is some work that relates specific ACT-R components to specific event-related potentials. For example, Simen et al. (2010) proposed that production selection by the procedural module, which forms the core of ACT-R, is associated with the Lateralized Readiness Potential. Another attempt at relating ACT-R to EEG involved linking specific aspects of ACT-R to the N100 and P300 event-related potentials (Cassenti et al., 2011). This study showed that the timing of the N100 during a motor task was associated with ACT-R’s prediction of completion of stimulus perception, while the onset of the P300 was associated with the decision to respond. It is not clear how these results generalize to other tasks and other ACT-R components.

In this study, I used a data-driven approach to find the electrophysiological correlates of a complete ACT-R model rather than individual modules. I focused on an attentional blink paradigm, for which a published ACT-R

Figure 2: Example of module activation probabilities for the ACT-R model of the attentional blink in one of the conditions (lag 3, blinked). Blue: imaginal (working memory) module. Green: visual module. Cyan: retrieval (from declarative memory) module. Red: production (procedural) module. The first spike reflects presentation of the fixation stimulus, which after 500 ms was followed by the stimulus train. For the visual, production, and retrieval modules, the bumps reflect processing of every individual stimulus in the train. The imaginal module activates only for the target stimuli. I used such module activations to create the ACT-R regressors that I correlated with the EEG data.
model exists (Taatgen et al., 2009) with corresponding EEG data (Martens et al., 2006). The attentional blink can be measured during a Rapid Serial Visual Processing task (Raymond et al., 1992; Luck et al., 1996) participants see a very rapid stream of visual stimuli, and have to detect what letters (“targets”) are presented in this stream of digits. The main finding in this task is that while participants can see two targets if those occur either far apart or in direct succession, they often fail to see the second target if it is separated from the first by only one or two intervening non-targets. This led to the idea that attention “blinks” after seeing the first target.

ACT-R accounts for the blink in attention by assuming there is an over-exertion of control. Each stimulus that is perceived enters the visual buffer. Next, a production is issued that asks the declarative module whether the perceived stimulus is a target (a letter) or not (a digit). When a visual stimulus is recognized by the declarative module as a target, it is stored for later report in the imaginal buffer, a cognitive resource representing working memory. When this imaginal buffer is not ready for consolidating targets because it is still busy writing the previous target to memory, it is impossible to consolidate the second target and therefore only the first target can be reproduced at the end of the stimulus stream, i.e., an attentional blink. Figure 1 shows a comparison of imaginal module activation for blinked and non-blinked conditions. During the blinks, the imaginal module fails to activate for the second target, and as a consequence the second target is not consolidated (compare the two bumps in imaginal module activity for the correct lag 3 trials to the single bump in imaginal activity for the incorrect or blinked lag 3 trials). When there is sufficient temporal distance between the two targets, as there is in the lag 8 condition, then there will always be two bumps in imaginal activation, and errors are caused by random failures to encode (due to, e.g., lapses of attention). As a consequence, for these trials the overall probability of imaginal activation is reduced for error trials relative to correct trials.

To be able to make predictions about the oscillatory correlates of the activation of ACT-R’s modules, I will discuss previous attentional blink-related EEG findings, and how those may correspond to activity of the ACT-R model. There have been three main findings in EEG studies of the attentional blink: a blink is associated with (1) an increase in the P3 event-related component (Vogel et al., 1998; Martens et al., 2006, the P3 is a positive potential occurring approximately 500 ms after a stimulus onset at parietal electrode sites), (2) a decrease in theta reset at the time of the second target
(T2), and (3) a decrease in gamma oscillatory synchronization at the time of T2 (Dehaene et al., 2003; Nakatani et al., 2005). The P3 is thought to reflect over-investment of attentional resources in the first target (T1) Slagter et al. (2007), or consolidation into working memory (Vogel et al., 1998). Note that the AB does not affect EEG components that come earlier in the stimulus processing pathway, such as the P1, N1, and N400 (Luck et al., 1996; Vogel et al., 1998). The reset of 4–9 Hz theta oscillations (i.e., aligning of the phase of theta oscillations across trials) at the time of the second target is thought to indicate that the system is ready for perceiving the second target (Slagter et al., 2009). This phenomenon may correspond in the ACT-R model to the preparedness of the imaginal module to encode stimuli into declarative memory. Gamma oscillations are periodic EEG activity in the 28–90 Hz frequency band. Gamma oscillations have been associated with a manifold of cognitive processes, including visual attention and consciousness (Varela et al., 2001). Dehaene’s Global Neural Workspace model (Dehaene et al., 2003) predicted a decrease in gamma synchronization for blinked stimuli. According to this model, when gamma synchronization decreases, it makes the visual stimulus less accessible to consciousness (Gaillard et al., 2009), and hence the participant will frequently fail to report that s/he has seen the stimulus. In terms of ACT-R, this too may reflect the impossibility for the target stimuli to enter the imaginal buffer.

Based on the observations discussed above, I predicted that activation of the imaginal module, which according to ACT-R is crucial for producing the attentional blink, would be correlated with the amplitude of 4–9 Hz theta oscillations. I further predicted that the gamma synchronization decrease that has also been associated with the attentional blink reflects a disconnection between the imaginal module and the retrieval module, such that items from the imaginal buffer cannot be transferred into declarative memory. For space limitations, I tested here only the first prediction—the association between the amplitude of theta oscillations and ACT-R module activation. To test this hypothesis, I compared ACT-R module activation time courses to EEG activity in all frequency bands, and asked (1) whether the theta band shows a specific activation pattern associated with imaginal module activation, and (2) what EEG channels are involved in that. Finally, if theta oscillations are indeed associated with ACT-R module activation, and if oscillatory coherence reflects communication, then the model should be able to make predictions about specific increases in oscillatory coherence at the time when different modules transmit information to each other.
Materials & Methods

Task: To find the electrophysiological correlates of ACT-R, I used a published model, accompanied by behavioral, and EEG data, from an attentional blink study (Martens et al., 2006). In this study, participants saw a very rapid stream of visual stimuli presented for 90 ms each. Their task was to report whether there are letters present in the stream, and if so, which letters those were. The data reported here are from the 11 participants in the study who showed a reliable attentional blink. The EEG data were collected at the University of Groningen with a 64-channel EEG system (Twente Medical Systems, Enschede, The Netherlands) at a sample rate of 250 Hz.

EEG pre-processing: EEG data were analyzed with the EEG toolbox, a set of Matlab scripts developed in the laboratory of Michael Kahana (e.g., van Vugt et al., 2010), as well as Fieldtrip (Oostenveld et al., 2011), complemented by custom-written scripts. I used the EEG toolbox to extract data for every channel separately. I then concatenated the time series for each trial lengthwise into one long time series (“features”) to be correlated with the ACT-R model time series (“regressors”—see below). I used 6-cycle Morlet wavelets (see van Vugt et al., 2007, for a comparison of different oscillation detection methods) to create representations of the EEG data in six distinct frequency bands: 2–4 Hz delta, 4–9 Hz theta, 9–14 Hz alpha, 14–28 Hz beta, 28–48 Hz low gamma and 48–90 Hz high gamma (van Vugt et al., 2010). I concatenated these frequency-transformed EEG data into long time series that matched the ACT-R time series in the same way as the raw EEG data.

To correlate ACT-R’s predicted module dynamics to EEG data, I created regressors (van Vugt et al., 2011, 2012) that could be used to find frequency bands and linear combinations of channels that correlated with this activity of interest. In this case, the data patterns of interest are activations of the ACT-R modules (visual, production, retrieval, and imaginal) that comprise the attentional blink model. In an ACT-R model, at every point in time a module (cognitive resource) can either be “on” (involved in information processing) or “off” (not involved information processing). This activation status was used to construct the regressors. I ran the attentional blink ACT-R model (Taatgen et al., 2009) 250–350 times (corresponding to the number of trials in the dataset) and computed the average activation for different model conditions: lag 3 and 8, and blinked and non-blinked trials. One can thus interpret these averaged module activations as the probability of a module being active. ‘Lag’ refers to the number of stimuli between the
first and second target (letter) in the digit stream that the participant has to remember. An attentional blink is likely to occur for lag 3, but not lag 8 trials. Trials in which the first target was missed by the participant were removed from the analysis because in that case it is not clear what the reason is for missing the second target if that also occurs.

For every trial that a participant did, I inserted the averaged module activation for the condition corresponding to that trial. This led to an activation time series for every ACT-R module that, after subsampling to the EEG sample rate (250 Hz), had the same length as the EEG data, and could therefore be used to regress the EEG time series on. The regression resulted in an estimate for every module of how well it correlated with each frequency band, and which channels were most strongly involved in this correlation. Instead of using a simple multiple regression, I used a multivariate canonical correlation analysis (CCA), which finds weights on the regressors (ACT-R time series) and features (electrode time series) that maximize the correlation between the electrode- and the ACT-R time series (van Vugt et al., 2012). Note that only the EEG data were wavelet-transformed—the ACT-R activation time courses were not.

**Across-subject analysis:** I combined the data across participants by appending the time series of the different participants in the time domain (Calhoun et al., 2001; Calhoun & Eichele, 2010). This resulted in a big matrix with 64 (number of channels) features and number-of-participants times timepoints-per-participant samples. Similar to previous work, I used only a subset (1/4th) of each participants’ data to run this CCA (van Vugt et al., 2012). The remaining data were used in a cross-validation analysis to test whether certain frequencies showed a higher correlation than the others (see below). I performed the CCA separately for every frequency band, but allowed linear combinations of regressors. This was helpful because the activations of some of the ACT-R modules were highly correlated. The CCA resulted in a set of correlations for every frequency band, one for each linear combination of regressors, and a corresponding set of electrode weights. The frequency bands with the highest correlations and the corresponding electrode weights form the EEG correlate of that particular linear combination of ACT-R modules. I assessed the significance of each canonical correlation by repeating the same analysis with a set of regressors in which the activation time courses of the respective modules were randomly displaced in time—thereby creating a distribution of random data. A significant canonical correlation should exceed the distribution of canonical correlations based on
100 iterations of performing the CCA with random data.

**Comparison between frequency bands:** I tested whether the correlation in a certain frequency band was higher than that in the other bands with a cross-validation analysis. For every participant I applied the weights obtained with CCA to the EEG data and ACT-R time courses that had not been used in the CCA. In that way, I obtained a distribution of regression coefficients (one for each participant) that I could compare between frequency bands (after having transformed the regression coefficients into z-scores with a Fisher transform), using methods I developed previously (van Vugt et al., 2012).

**Event-related averages:** To interpret the canonical variates, I computed event-related averages of the oscillatory correlates of ACT-R module activation. This was done by applying the electrode weights resulting from the CCA to the time courses of oscillatory power and computed averages separately for each of the four trial types (lag 3–correct, lag 3–error, lag 8–correct, lag 8–error). To prevent distortions of the waveform, I removed any trial that had a kurtosis larger than 4 (Delorme & Makeig, 2004) or an average EEG amplitude larger than 70 µV. I verified by visual inspection that these thresholds removed most artifacts while at the same time retaining most non-artifactual EEG. To remove confounds of differences in overall amplitude between participants and between frequency bands, I z-scored all data before averaging.

**Coherence analysis:** Coherence is computed by normalizing the summed cross-spectral density of the EEG signal between two electrodes in a desired frequency band by their respective power Thatcher et al. (1996). This effectively produces a correlation in the frequency domain. To test the hypothesis that the ACT-R modules communicate through coherence, I compared coherence at 7 Hz (theta band) between the sets of electrodes comprising the two canonical variates between time points at which the model predicted information transfer and time points at which there should be little information transfer. Variates 1 and 2 consisted of electrodes P2, P10, O10, O1, AFz, Fz, Fpz, and FT10. Specifically, first I tested whether there was sign of communication between visual and production modules. This communication should happen during time windows right after the activation peak of the visual module and before the peak of the production module; see Figure 2), but not so much during the peak of the visual module, approximately 40 ms earlier. The coherence analysis was done within-subjects, and the across-subject t-statistic was computed on these within-subject effects. Having established this basic effect, I further examined whether there was a
Table 1: Cross-correlations between the ACT-R module (cognitive resource) time courses, averaged across participants. The activation time course of the imaginal module is quite different from the other modules, see Figure 2.

<table>
<thead>
<tr>
<th></th>
<th>Imaginal</th>
<th>Production</th>
<th>Retrieval</th>
<th>Visual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Imaginal</td>
<td>1.0000</td>
<td>0.3922</td>
<td>0.3057</td>
<td>0.3880</td>
</tr>
<tr>
<td>Production</td>
<td>0.3922</td>
<td>1.0000</td>
<td>0.2138</td>
<td>0.5046</td>
</tr>
<tr>
<td>Retrieval</td>
<td>0.3057</td>
<td>0.2138</td>
<td>1.0000</td>
<td>0.5238</td>
</tr>
<tr>
<td>Visual</td>
<td>0.3880</td>
<td>0.5046</td>
<td>0.5238</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

The basic behavioural and EEG data for this task were reported in Martens et al. (2006), who demonstrated a classic attentional blink effect (dip in accuracy for the second target letter when it followed the first target letter with only 1 or 2 items in-between). This dip in performance was accompanied by an increased P3 EEG component for blinked compared to non-blinded trials.

Results

The basic behavioural and EEG data for this task were reported in Martens et al. (2006), who demonstrated a classic attentional blink effect (dip in accuracy for the second target letter when it followed the first target letter with only 1 or 2 items in-between). This dip in performance was accompanied by an increased P3 EEG component for blinked compared to non-blinded trials.

Canonical correlation analysis

Figure 2 shows an example of average ACT-R module activation on a single trial for the lag 3/blinked condition. These activation time courses were used to create regressors that could be used to extract corresponding patterns from the EEG data. I correlated these regressors with both the raw EEG time series and oscillatory time series in the frequency bands of interest (see Methods). Figure 3 shows the resulting canonical correlations between two linear combinations of modules and EEG activity. The first canonical variate primarily reflects the production and retrieval modules, while the second canonical correlate primarily reflects the imaginal module. This pattern of weights is not surprising given the high correlations between the activations of the visual, retrieval and production modules, which effectively turns them
into a single time course for the purpose of finding neural correlates of ACT-R (Table 1; see also Borst et al., 2011, for a discussion). The remaining two canonical variates had correlations with the EEG data that were too low to be considered (lower than 0.06), and which did not exceed random noise (see below).

To verify whether the obtained canonical correlations were not due to random noise, I applied a randomization analysis. The first canonical variate, reflecting primarily the production and retrieval modules, was significantly different \( p < 0.02 \) from a distribution of canonical correlations based on random data for all frequency bands except for raw EEG data \( p = 0.63 \). The second canonical variate, reflecting primarily the imaginal module, was significantly different \( p < 0.01 \) from correlations based on random data in all frequency bands. The existence of only two canonical variates in the data agrees well with the clusters of inter-correlations between the regressors: the imaginal module on the one hand and the retrieval, visual and production modules on the other.

**Interpretation of canonical variates**

To interpret the obtained canonical variates, I created time courses of both ACT-R module activations and oscillatory EEG weighted by the canonical variate coefficients in the relevant frequency bands. Figure 4(a) shows the weighted combination of ACT-R activations that reflects the first canonical variate. There is an increase in amplitude for the stimulus presentation period and little differentiation between the four conditions (lag 3 vs. lag 8; blink vs. non-blink). I therefore refer to this variate as the “stimulus identification” variate. The second canonical variate loaded predominantly on the imaginal module, thus likely reflecting processing of the target stimulus. Indeed, the time course of this canonical variate (Figure 4(b)) shows no particular modulation by the stimulus train, but there is a clear bump after each of the target stimuli (T1 and T2)—at least when the second target is not blinked. For this reason I refer to the second variate as the “target consolidation” variate. What is most salient in these time courses is the difference between lag 3 and lag 8; where lag 8 shows two distinct target peaks, those are merged in the lag-3 case. This is pattern is the same as what the imaginal module shows (Figure 1), and what results in the attentional blink.
Frequency specificity

For both of the canonical variates, the highest correlations with EEG activity seem at first eye to occur with the 2–4 Hz delta and 4–9 Hz theta band. To substantiate this claim, I used a cross-validation analysis (see Methods), to test whether there were certain frequency bands that showed a higher canonical correlation than the other frequency bands. The mean of the correlation between the ACT-R variates and the delta band was higher than the correlation with all other frequency bands for both variates \( t(75) = 4.71 \) and \( t(75) = 4.43, \ p < 0.001 \) for variate 1 and variate 2, respectively). The mean of the correlations between ACT-R variates and theta power was only higher than the other bands for variate 1 \( t(75) = 3.59, \ p < 0.001 \). All other comparisons had \( t(75) < 1.81, \ (p > 0.07) \).

Scalp topographies

I further examined the scalp topographies associated with the canonical variates in the different frequency bands. While the frequency bands that have the highest correlations with the ACT-R time courses appear to be quite similar across the two canonical variates (Figure 3), the topographies in Figure 5 show that the channels belonging to the stimulus identification variate (variate 1) and the ones belonging to the target consolidation variate (variate 2) are associated with different subsets of EEG channels. The first variate was primarily associated with posterior (occipital and temporal) 2–4 Hz delta and 4–9 Hz theta oscillations. The second variate was primarily associated with parietal and frontal 2–9 Hz delta/theta oscillations.

Event-related EEG time courses

I then examined the time courses of the EEG-components of the canonical variates, separating the different frequency bands. Since the stimulus identification variate showed significant correlations with both 4–9 Hz theta and with higher frequencies, Figure 6 shows the weighted EEG time courses in these two bands. Theta power increases for all trial types over the course of stimulus presentation, and slight bumps are discernible for the two targets. These bumps are less pronounced for the blinked trials in which the second target is missed. A similar stimulus-stream-related increase in oscillatory power is apparent for the gamma band. Activity in this frequency band changes fast enough to increase with the presentation of individual stimuli (which are presented at a rate of 11.1 Hz; see Figure 6(b)).
A somewhat different picture is painted by the time course of the target consolidation canonical variate (Figure 7). For this variate, 4–9 Hz theta power does not increase and decrease with onset and offset of the stimulus stream, but rather increases more selectively after each target. For lag 3, the two target-related theta power peaks appear to be merged, while for lag 8, they can be distinguished. The second target-related peak appears to be missing for the blinked trials (red and magenta), as one would expect if this variate is involved in consolidating target stimuli, which takes place specifically for targets in non-blinked trials and is absent for targets that are blinked.

**Coherence between canonical variates**

Having highlighted the oscillatory correlates of ACT-R’s different modules, I then wanted to examine the potential for this method to explain patterns of oscillatory coherence. Could the observed correlates of ACT-R resources be communicating with each other through coherence (Fries, 2005)? To answer this question, I generated—based on the ACT-R module time courses—a set of time points at which I expected high volumes of communication (and therefore coherence). These were time points at which the model would require information transfer between the modules. I contrasted those periods with other periods at which the model predicted little communication. For example, the visual module and the production module are activated sequentially, and they should transmit information about the identity of the perceived stimulus (to allow the retrieval module to determine whether the perceived stimulus is a target to be encoded into memory). This implies that according to the communication-through-coherence hypothesis there should be high coherence just after the peak activation of the visual module and before the peak activation of the production module (Figure 8). I computed coherence for a set of electrodes in the regions of interest defined by the theta topographies (Figure 5), and contrasted theta-coherence estimates between time points of hypothesized high communication and time points of low communication. Figure 9 shows the pairs of channels that exhibit significantly ($t(10) > 2$) increased coherence for periods where the model predicts high communication between the visual and production modules relative to the time periods when there should not be such communication.

Having established that proof of principle, I further investigated whether a pattern of information transfer more crucial for the attentional blink could also be observed in scalp EEG data. A second prediction made by the ACT-R
model is that after the appearance of T2, its identity should be consolidated into the imaginal buffer for later report. When this fails, the second target is missed—the attentional blink. To test this prediction, I compared coherence at the theta frequency between successfully reported and blinked targets; where successful report should be associated with larger coherence. Indeed, Figure 10 shows that coherence between a set of primarily posterior and frontal channels is larger for successfully reported T2 relative to missed T2.

Discussion

My aim was to show how cognitive architectures can be helpful for investigating the role of oscillations in cognition. Using my recently-developed canonical correlation method for relating brain oscillations to models of cognition (van Vugt et al., 2012), I showed that the activation of different cognitive resources from the ACT-R cognitive architecture correlate with specific sets of EEG channels. The first canonical variate reflected stimulus identification, and comprised mainly ACT-R’s production and retrieval modules. This variate was associated with posterior theta oscillations. A second canonical variate reflected target consolidation, and comprised mainly ACT-R’s imaginal module (working memory resource). This variate was associated with parietal theta oscillations. The observed topographies are in line with previous fMRI localizations of the imaginal module in the intraparietal sulcus (Anderson et al., 2008; Borst et al., 2011). I finally showed how this method could be used to interpret patterns of coherence. In particular, theta coherence between posterior and temporal channels could be reflection transmitting information about stimulus identity, and theta coherence between frontal and posterior channels that just after T2 presentation, could reflect target consolidation.

It should be acknowledged that the mapping between ACT-R modules and oscillatory EEG data described here is preliminary, since it is based only on data in a single task. It may be argued that many events in this task are strongly stimulus-driven, and any model that describes the task could account for this. While this is true, more naive models that merely describe stimulus and response patterns could not be used to simulate patterns of behaviour and make novel predictions, as this model has done (Taatgen et al., 2009; Wierda et al., 2010). Using ACT-R, we were able to interpret patterns of oscillatory coherence at times predicted by the model. To further validate the EEG localizations of the ACT-R modules and to disentangle the oscillatory-
tory correlates of the visual, production, and retrieval modules, the analysis
presented here should be applied to data from other tasks in which these
modules’ activations are less tightly coupled with each other. Such uncou-
pling can be done by using tasks in which the production, retrieval and visual
modules are not as highly correlated as they are in the attentional blink task,
e.g., a task that requires memory search independent of visual stimulation.

Another area that warrants further investigation is modeling individual
differences. The work presented here is based entirely on a group model of the
cognitive task. Taking into account individual differences could solidify our
confidence in the mapping between modules and EEG activity in the follow-
ing way. If individual differences are modeled in ACT-R (e.g., Lovett et al.,
2000) and if those individual differences correlate with individual differences
in those participants’ electrophysiology, then this increases confidence in the
EEG–ACT-R-module relation (see van Vugt et al., 2012, for an application
of this approach to perceptual decision making).

The work presented here has several implications for research into the
role of oscillations in cognition. First, it pointed to a new function for theta
oscillations, that is, in the identification of stimuli (for posterior channels),
and memory consolidation of to-be-remembered targets (for fronto-parietal
channels). Second, the cognitive architecture approach to model-based neu-
roscience is a gateway towards more studies into the role of oscillatory coher-
ence in cognition. Oscillatory power and coherence may be correlated, but
this is not necessarily so (Fries et al., 1997). For that reason, we introduced a
new interpretation of coherence. The model-based analysis of coherence pre-
sented here provides a principled way to look for patterns of functional con-
nectivity in EEG activity. If coherence reflects information transfer between
cognitive resources (Buzsáki, 2006; Singer, 1993), then increases in coherence
should occur in specific frequency bands and between the sets of electrodes
that correspond to the respective resources. For the modules shown in Fig-
ure 8, for example, I predicted that after every stimulus presentation, there
should first be increased coherence between the neural correlates of the vi-
sual and the production modules (Figure 8), and subsequently between the
production and retrieval modules. When a target is consolidated successfully,
but not when it is not, there should be increased coherence between the produc-
tion and the imaginal modules. Also this second prediction was verified.

In conclusion, I have outlined novel methods to use cognitive architec-
tures in understanding the role of oscillations in cognition. I have applied
those to an attentional blink task, and demonstrated an association between ACT-R modules and brain oscillations in different channels and frequency bands—the imaginal module (target consolidation) was associated with parietal theta oscillations and the visual/production/retrieval modules (stimulus identification) with posterior theta oscillations. I argue that these methods can be an important tool for understanding the role of oscillatory coherence in cognition.

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Figure 3: Canonical correlation between linear combinations of ACT-R module activations and EEG time courses for raw EEG (“EEG”), 2–4 Hz delta (“D”), 4–9 Hz theta (“T”), 9–14 Hz alpha (“A”), 14–28 Hz beta (“B”), 28–48 Hz low gamma (“G1”) and 48–90 Hz high gamma (“G2”) activity. (a) Profile of canonical correlations across frequency bands for the first two canonical variates. White dots indicate the 97.5th percentile of the distribution of canonical correlations based on random data. (b) Weights on the different regressors for the first two canonical variates averaged over frequency bands. The first canonical variate reflects primarily the production (Pr) and retrieval (Re) modules. The visual (Vi) module is not strongly represented in either of these variates.
Figure 4: Time courses of linear combinations of ACT-R module activations that comprise variate 1 (on vs off-task/stimulus identification) and variate 2 (target consolidation) in the 4–9 Hz theta band. The four conditions are shown in different colors: lag 3 non-blinked blue; lag 8 non-blinked: black; lag 3 blinked: red; lag 8 blinked: magenta. The times at which the first (T1) and second target (T2) are presented are indicated in the figure (T2 in blue for lag 3 and in black for lag 8).

Figure 5: Topographical representation of the correlation between ACT-R module activation and EEG. Variate 1 primarily reflects stimulus processing for the purposes of identification, which is done by the production and retrieval modules; variate 2 primarily reflects target processing for the purposes of consolidation and subsequent report, which is done by the imaginal module. Plotted are the magnitudes of the canonical correlation weights across the brain for the canonical correlation between ACT-R time series and EEG activity in the respective frequency band. Red positive weights; blue: negative weights.
Figure 6: *Time courses of 4–9 Hz theta (left) and 28–48 Hz low gamma band activity corresponding to the stimulus identification canonical variate.* The times at which the first (T1) and second target (T2) are presented are indicated in the figure; 0 ms is the onset of the stimulus stream. Time courses for lag 3 trials are in blue (correct) and red (blinking), while time courses for lag 8 trials are in black (correct) and magenta (blinking).

Figure 7: *Time course of 4–9 Hz theta activity corresponding to the target-consolidation canonical variate.* The times at which the first (T1) and second target (T2) are presented are indicated in the figure; 0 ms is the onset of the stimulus stream. Time courses for lag 3 trials are in blue (correct) and red (blinking), while time courses for lag 8 trials are in black (correct) and magenta (blinking).
Figure 8: *Example of predictions for neural correlates of information transfer between modules in the attentional blink task* (adapted from Taatgen et al., 2009). At the time of processing the letter “A” by the visual and production modules, there should be a specific increase in synchronization in the theta band between the channels corresponding to the stimulus identification and target consolidation variates. These sets of channels were based on Figure 5.

Figure 9: *Increases in coherence during model-predicted communication between visual and production modules*. The visual module sends information to the retrieval module through the production module to determine the identity of the perceived stimulus.
Figure 10: Larger coherence during successfully consolidated relative to unsuccessfully consolidated targets during predicted communication between production and imaginal modules. The production module sends information to the imaginal module to consolidate the target for subsequent report.