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# Simulating the Paced Serial Auditory Addition Test after Traumatic Brain Injury

## Background

The Paced Auditory Serial Addition Test (PASAT) has been used in a variety of applications, mostly as a measure of attention, speed of information processing, and working memory (Tombaugh, 2006). The test involves presenting a list of single-digit numbers to the participant at evenly-spaced intervals. Each time a digit is presented, the participant must respond with the sum of the two most recently presented digits. For example, if the digit '3' is presented, followed by '7', the participant should respond '10'. If a '5' is presented next, the participant should respond '12'. Participants must respond before the next digit is presented in order for their response to be counted as correct. Digits are typically presented at an inter-stimulus interval (ISI) of 1.2s, 1.6s, 2.0s, or 2.4s. The duration of each digit presentation is approximately 0.4s. The test is run as a sequence of 61 digits, resulting in 60 responses. The PASAT is scored as the percentage of the 60 responses the participant got correct. In the original version of the test, digits are presented through auditory stimuli, but visual stimuli have been used in later cases (Diamond, DeLuca, Kim, & Kelley, 1997) The PASAT generally measures attention processes, verified by correlated scores with other tests measuring attention (Tombaugh, 2006). In addition to attention, the PASAT also involves auditory and verbal processing, working memory, basic number manipulation, and task management under time constraints. Some consider the PASAT to measure the rate of information processing (Gronwall & Sampson, 1974), due to the number of different cognitive processes involved.

Since there are multiple cognitive processes involved, the PASAT has been used to provide insight into cases where general information processing or attention may be impaired. The first clinical application of the test was towards detection of traumatic brain injuries (TBI), as well as a measure of recovery from TBI (Gronwall, 1974). Initial studies showed performance on the PASAT is impeded following TBI, and scores slowly return to baseline in the following days as the subject recovers. As a result, the PASAT is one of the recommended tests used to detect a sport-related concussion (Guskiewicz, Bruce, Cantu, & Ferrara, 2004). Athletes would take the test prior to the season to establish a personal baseline, and testing during the season should reveal a concussion if their scores drop.

Since its introduction, a variety of studies have looked at PASAT performance after a TBI. However, comparison across studies is difficult, due to high variance in control group scores, and the severity of the TBI studied. TBIs are classified based on a variety of factors, such as loss of consciousness, amnesia, and other symptoms (Leininger, Gramling, Farrell, Kreutzer, & Peck, 1990). I have grouped the TBIs previously studied into two groups: mild and severe. The mild grouping contains any data labelled as a mild TBI, but there is no guarantee the TBIs within the grouping are very similar. The severe grouping contains any TBIs described as moderate to severe, which includes a wider range of TBIs. In order to compare across studies, I have looked at the difference between the control group scores and the mild or severe scores for each study for each ISI. The average scores and differences are shown in Table 1. There are 4 studies within the mild group, and 5 studies within the severe group, as taken from studies previously covered

*Table 1: Averaged PASAT Scores for Mild, Severe TBI*

| | Mild TBI | | | | Severe TBI | | | |
|---|---|---|---|---|---|---|---|---|
| ISI (s) | 2.4 | 2.0 | 1.6 | 1.2 | 2.4 | 2.0 | 1.6 | 1.2 |
| Control | 76.75 | 69 | 56.75 | 41.25 | 81.8 | 73 | 63.8 | 47.4 |
| TBI | 66.8 | 59 | 47.8 | 32.2 | 53.4 | 44.6 | 36.8 | 26.4 |
| Difference | 9.95 | 10 | 8.95 | 9.05 | 28.4 | 28.4 | 27 | 21 |

by Tombaugh (2006). The difference scores for the average scores per ISI are fairly consistent across ISIs, showing a decrease in performance of about 10 in mild cases and a difference near 25 in the severe cases.

There has also been extensive work into determining the specific neural regions involved in each aspect of the PASAT, but due to the variety of processes involved many regions show potential relation to the PASAT and it is difficult to assign specific functions to each area. However, some of the general areas involved with the PASAT have been identified (Lockwood, Linn, Szymanski, Coad, & Wack, 2004). The temporal lobe consistently shows activation in regions responsible for verbal and auditory processing, and motor systems show activation of facial and mouth muscles, correlating with the input/output systems used during the test. The anterior cingulate cortex is also consistently detected, and is thought to be responsible for mediating attention to the test. Working memory systems are thought to be part of the dorsolateral prefrontal cortex (DLPFC). Number manipulation and single-digit addition processes are thought to be centered in the parietal and occipital lobes (Pesenti, Thioux, Seron, & De Volder, 2000). Finally, studies have also shown significant activation in the cerebellum, although the specific purpose of the cerebellum in relation to the PASAT is unknown [cite].

Recently, researchers have been exploring developing models of the neural damage produced by a TBI. This damage can come in many forms, as TBIs can result in differences in blood flow, synapse function, axonal damage, and hormone production (Graham et al., 2014). Axonal damage is seen in TBIs of any level of severity, with the number of damaged axons increasing with the severity of the injury (Graham et al., 2014). Axonal damage has also been shown to correlate with decreased cognitive performance in mild TBIs (Niogi et al., 2008), and models of the damage distribution throughout the brain have been created (Wright, Post, Hoshizaki, & Ramesh, 2013). Using the example TBI from Wright, Post, Hoshizaki, & Ramesh (2013), the amount of axonal damage in the regions associated with the PASAT can be determined. The relevant areas and the amount of damage is shown in Table 2. The areas affected in the axonal damage model do not directly map onto the regions used by the PASAT, so I used the average damage for all nearby areas. The auditory cortex (superior temporal gyrus) and anterior cingulate cortex did not show any damage in the model.

## Project Overview

The goal of this project is to develop a neural model capable of performing the PASAT, and damage the model to replicate the impairment caused by a TBI. The main focus of the neural model will be the working memory structure used to remember the two most recently presented

*Table 2: Estimated White Matter Damage due to TBI*

| PASAT Region | Damaged White Matter Regions | Average Damage (%) |
|---|---|---|
| Temporal Lobe | None | 0 |
| Anterior Cingulate | None | 0 |
| DLPFC | Middle Frontal Gyrus | 44 |
| Parietal, Occipital Lobes | Postcentral Gyrus, Superior Parietal Gyrus, Precuneus, Supramarginal Gyrus, Angular Gyrus | 40 |

presented digits and the added sum. The model will also assume memorized single digit addition, and will be compared to PASAT norms for age and education levels (Diehr, Heaton, Miller, & Grant, 1998) which are likely to have fully memorized single digit addition. The model will then be damaged based on the axonal damage model outlined in Table 2. The resulting loss in performance will be compared to the expected loss outlined in Table 1.

## System Description

The PASAT involves many different cognitive processes, such as auditory and verbal processes, attention, task management, addition, and memory. I have focused primarily on the memory process, as well as the addition and task management processes. The auditory and verbal processes are essentially the input and output processes for the task, which will be simplified into an input state driven by an external input signal, and an output state containing the system's response. The attention process is essentially ignored, as the model is always working on the PASAT and does not get distracted. The memory process is simulated using a recency-based memory, and contains a list of the numbers previously presented. These numbers are bound to positional information to distinguish successive digits. The addition process is simulated using an associative memory which serves as a memorized mapping of two digits to their sum. In terms of the neuroanatomical correlates to these subsystems, he memory subsystem corresponds to the DLPFC and the addition subsystem corresponds to number processing primarily in the parietal lobe. Task management is done using action rules which guide the model through the steps needed to complete the PASAT, through thalamus and basal ganglia models.

The neurons used in the simulations are the default leaky-integrate-and-fire neurons used in Nengo. Due to the high-level anatomical understanding of the PASAT, we do not know the details of the types of neurons used in the brain. Therefore, model development will rely on high-level architecture decisions instead of neuron-level details. The parameters of the model architecture, such as dimensionality and memory size, are tuned to reach the desired levels of functionality. Semantic pointers are used to represent all numbers and position encodings.

The working memory module must represent at least 3 numbers at any point in time: the most recent digit, the second most recent digit, and the sum of those two digits as retrieved from the addition module. The sum is stored in the working memory with the recently presented digits to model interference between the presented digits and the sum, since participants would consciously think of the sum before they answer. The memory will contain the vector $m =$

$pos_n \circledast num_n + pos_{n-1} \circledast num_{n-1} + ans_n \circledast num_{sum} + noise$, where $num_i$ are vectors representing numbers, either those presented or the sum of the presented numbers, and $pos_i$ and $ans_i$ are vectors used to encode the numbers as either positions in the sequence or the current answer to be output. $noise$ is the residual effect of previous numbers in the sequence. The memory is driven by either the input number or the next sum, as directed by the task management actions. When the memory is not being driven, it must remain constant, satisfying $\dot{m} = 0$.

The addition module must translate two input number representations into an output representation using a specified mapping. This is done by transforming the two inputs into a single input, which is fed through a heteroassociative memory. The input representations are combined using circular convolution, resulting in a single input representation of $in = num_n \circledast num_{n-1}$. This value is mapped to the sum using the heteroassociative memory. For example, if the inputs are $ONE$ and $THREE$, $in = ONE \circledast THREE$, and the heteroassociative memory should map $ONE \circledast THREE \rightarrow FOUR$. The heteroassociative memory uses a winner-take-all output to reduce noise in the resulting sum representation.

Three autoassociative memories are used to cleanup the output of the memory system. These memories map the input to the number representation most similar to the input. For an input $number\_in$, the system maps $number\_in \xrightarrow{\text{max\_similarity}} number$. For example, if the input representation is most similar to $ONE$, the output of the system should be $ONE$. These cleanup memories are used to retrieve the most recent number, the second most recent number, and the sum from the working memory.

The overall system architecture is shown in Figure 1. The input signals consist of the next number being presented, the positional input, and a control signal. The number input is convolved with the position input and connected to the working memory, and the thalamus-basal ganglia circuit control when to drive the working memory with the input, based on the control signal. The

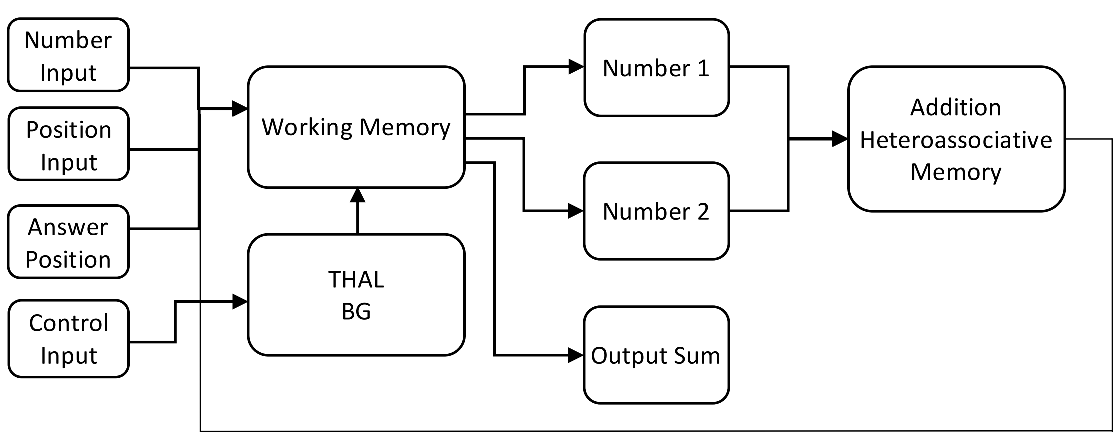


*Figure 1: System Architecture. The number, position, and control inputs are controlled signals assumed to be computed upstream in the brain. The output sum would be fed to speech processing areas for further output.*

inverses of the current and previous position representations are convolved with the working memory, and the result fed into the cleanup memories for the most recent and second most recent numbers. The outputs of the cleanup memories are convolved and fed into the heteroassociative memory used for addition. The resulting sum representation is convolved with an $ANSWER$ position representation and fed back into the working memory. The working memory is convolved with the inverse $ANSWER$ representation, and fed into a cleanup memory for the output sum.

## Design Specification

The nature of the PASAT creates some restrictions on the model. First, the input numbers are all single digit numbers (1 to 9), so the output can range from 2 to 18. Therefore, semantic pointers for the numbers 1 to 18 are required. Additionally, to support the heteroassociative memory, semantic pointers for all valid combinations of the input numbers are required. Since circular convolution is commutative, there are $\sum_{i=1}^{9} i = 45$ semantic pointers required for the convolved pointers. Additionally, the full PASAT contains 61 numbers, so there must be 61 positional encoding semantic pointers. These encodings are created using an initial $POSITION$ pointer along with a $NEXT$ unitary pointer to advance the position pointer. There is also an $ANSWER$ pointer that is encoded with the $NEXT$ unitary pointer to denote the current answer to be output, creating 60 different answer encodings. This results in 185 different semantic pointers which will be fed through either the working memory or the associative memories. In order to allow recovery from the working memory through the cleanup memories, similarity must be minimized. 512 dimensions was chosen, as it results in no created semantic pointers with similarities above 0.1.

The range of pointers allowed by the cleanup memories is also limited based on the PASAT. The output of the cleanup memories for the previously presented numbers is restricted to single digit numbers only, and the output of the cleanup memory for the output sum is restricted to only output numbers between 2 and 18. The input numbers range randomly between 1 and 9, and can be presented for up to 0.4s, as in the PASAT. The full 0.4s is likely not needed to commit the number to memory, as in the PASAT the 0.4s would also include auditory processing and transformations to the number representation. The position signal ranges from $POS1$ to $POS61$ over the course of the test. The control signal is $INPUT$ while a number is presented, and 0 otherwise.

The test also provides some constraints on the working memory structure. Since the test requires the participant to recall the two most recent items, the working memory structure does not need to include primacy effects. Primacy would only help with recall of the first numbers, and as the test proceeds the effects would become minimal. Therefore, the working memory can be implemented as a recency memory. The memory also needs to be robust enough to remember the two most recent items as well as the sum with minimal decay, so a large number of neurons will be needed. The number of subdimensions and neurons per dimension will be tuned based on functionality.

## Implementation

The addition module was a relatively simple module to implement. The module consists of an associative memory which takes the convolution of two number representations and maps it to the number representation corresponding to the addition of the two numbers. The associative memory uses a winner-take-all output to force only one output. The input representations are the output of cleanup memories which output single digit number representations. Figure 2 shows the similarity of the addition module output with all number representations. Two numbers were passed through two cleanup memories for t = 0.0 to 0.2 and t = 0.4 to 0.6. A shown, the addition module outputs a high level of similarity for only one sum. Figure 3 shows the input signals as well as the output signal during the same experiment. The module adds $TWO$ and $TWO$, outputting $FOUR$ with 95% similarity approximately 0.08 seconds after the inputs are initialized. Once the inputs are turned off, the module begins to lose the value after 0.3 seconds, with the similarity reaching 0.1 within 1 second of the inputs being turned off. The inputs are restarted as $ONE$ and $SEVEN$, and the model outputs $EIGHT$ within 0.11 seconds.

The time to generate an output is an acceptable period of time, as it is not instantaneous, but is also not so slow as to appear incorrect relative to human addition speeds. This module does not model the auditory and verbal processing involved when responding to a single digit addition question, so it is reasonable that single addition takes approximately 0.1 seconds to look up.

The working memory module uses a state with a feedback connection strength of 1.0 to create a recency-based memory. The input numbers are encoded with positional information and used to drive the memory. The positional information is provided by an external signal, as I was unable to get a neural circuit working to advance the position every time a number is provided. Numbers

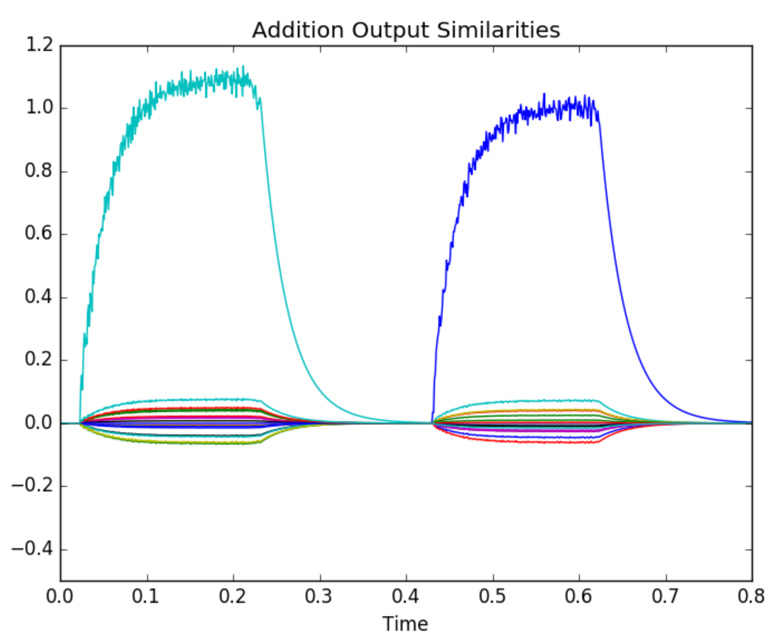


*Figure 2: Addition Module Output Similarity to Number Representations. Inputs were driven for t = 0.0 to 0.2 and t = 0.4 to 0.6. The addition module provides one number as output. Similarity was computed against all 18 number representations.*

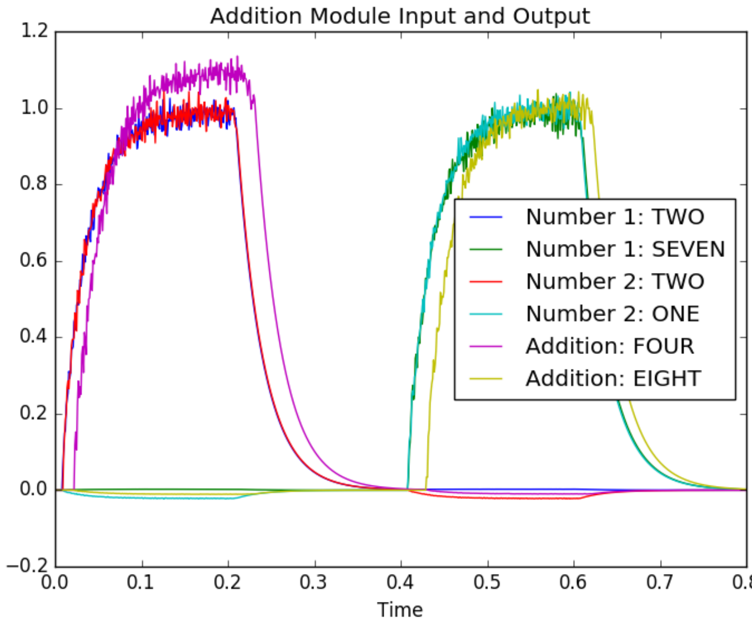


*Figure 3: Addition Module Input and Output. Inputs are driven from t = 0.0 to 0.2 and t = 0.4 to 0.6. The module is able to add both numbers and provide and output with a 95% similarity to the desired output in approximately 0.1 seconds.*

are retrieved from the memory by convolving the memory with the inverse of the desired position. The retrieved value is used as input to a cleanup memory to ensure a number representation is output. Figure 4 shows the most recent and second most recent numbers as output from the cleanup memories over the span of 1.6 seconds. The memory is driven first by $POSITION_1 \circledast THREE$, and after approximately 0.15 seconds the cleanup memory is showing an output with 95% similarity to $THREE$. At 0.2 seconds the input is turned off, but the value $THREE$ is remembered. At 0.4 seconds the next number $FIVE$, is provided. The memory is now driven by $POSITION_2 \circledast FIVE$. Again, after around 0.15 seconds the cleanup memory is properly outputting $SIX$. The cleanup memory for the second most recent number reaches $THREE$ within 0.1 seconds of the inputs changing. The input of $POSITION_2 \circledast FIVE$ is held until t = 0.6 seconds. The input at t = 0.8 seconds becomes $POSITION_3 \circledast NINE$, and as the memory is driven further towards the input the decoding of the second most recent number dips slightly in magnitude. However, once the input is removed, the cleanup memory begins to rebound back to a higher level. The low recall levels of $POSITION_2 \circledast FIVE$ from t = 1.0 to 1.2 is indicative of a transient memory error that could lead to human-like scores on the PASAT.

In addition to storing the previous numbers in working memory, the current answer should also be stored in working memory. To facilitate this, answers are stored using a similar encoding to position encodings, where $ANSWER_i$ is the pointer $ANSWER$ convolved with $NEXT$ $i$ times. A demonstration of both numbers and answers being stored in the working memory is shown in Figure 5. The input sequence is $SIX \rightarrow TWO \rightarrow ONE \rightarrow FOUR$, with inputs being driven for 0.2 seconds at t = 0.0, 0.6, 1.2, and 1.8. An answer signal is provided, which cycles through $ONE \rightarrow TWO \rightarrow THREE \rightarrow FOUR$, and driven for 0.2 seconds at t = 0.2, 0.8, 1.4, and 2.0. Including the answer in the memory has a significant impact on recall of the second most recent number, as shown by the almost completely lost $TWO$ in the graph. However, the input and answers may not need to be driven for a full 0.2 seconds, which could improve recall of the second most recent number. Some forgetting is to be expected, as the control groups shown in Table 1 had maximum scores around 80%.

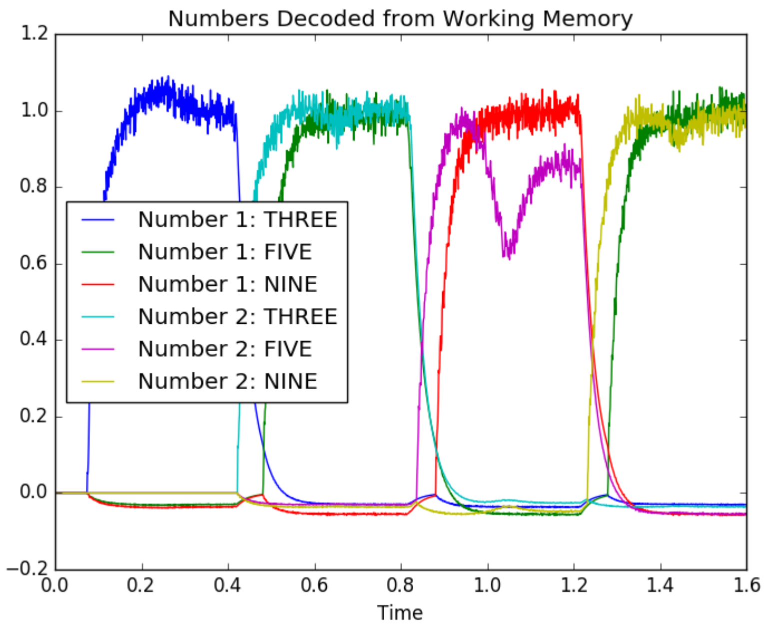


*Figure 4: Decoding the Most Recent (Number 1) and Second Most Recent (Number 2) Numbers from Working Memory.*

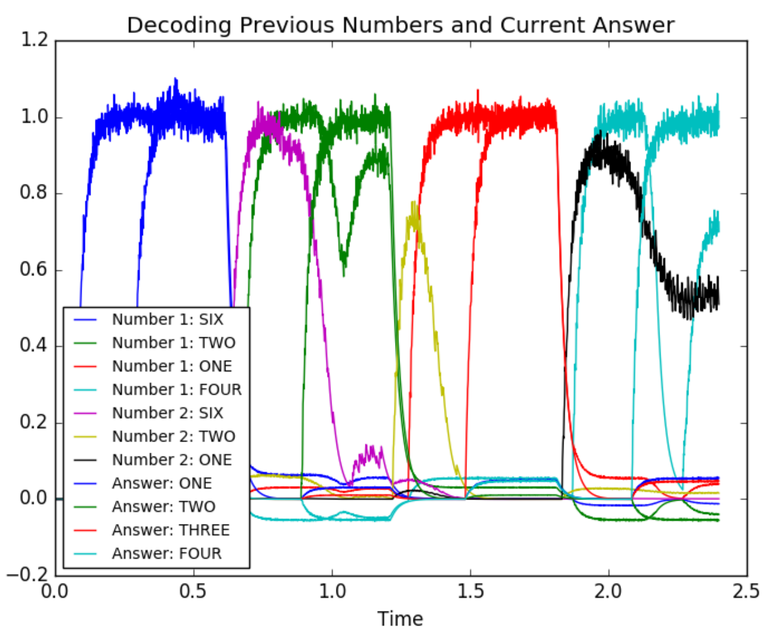


*Figure 5: Decoding the Current Answer Alongside Previous Numbers*

The next step is to place the output of the addition module into the working memory instead of the external answer signal. The working memory input will either be the input number or the output of the addition module, so the input needs to be controlled to select between the two. This is done using a thalamus-basal ganglia model to control the sequence of actions used to perform the PASAT. To simplify the model while testing driving the memory using the addition model, a set of external control commands are used to indicate which action to take at fixed timing intervals. The set of actions are shown in Table 3. Each phase of the control plan lasts a fixed period of time. During the input phase, the memory is driven by the input number convolved with the current position. During the answer phase, the memory is driven by the result of the addition module convolved with the current answer position. Finally, a wait phase allows the cleanup memories to settle and converge on a stable state.

The result of feeding the addition result through the working memory is shown in Figure 6. The first number is input from t = 0.0s to 0.3s, and the second number begins input at t = 0.3s. At t = 0.5s the answer phase begins, and the working memory is driven by the result of the addition module. As shown, the addition module output has a very high similarity to the correct number, $THIRTEEN$, but the decoded output from working memory does not see any similarity to $THIRTEEN$. Instead, the decoded output is most similar to $SIXTEEN$, which appears to be a side effect of the second input number, as the similarity to $SIXTEEN$ begins to increase around t = 0.3s. I am not sure why $THIRTEEN$ does not show up in the decoded output, as I ran out of time while trying to identify the problem. Driving the memory with the unencoded output of the addition module (i.e. only $THIRTEEN$, and not $THIRTEEN \circledast ANSWER_i$) appears to produce some trace of the sum in the memory, although it is incredibly unreliable as time goes on, since there is no differentiation of successive sums. Once the sum is bound to another pointer using convolution, all traces disappear from the memory.

Instead of using a fixed control signal, a more fluid control model could be used to guide PASAT completion. A timed control signal is useful for testing, but has no similarity to what would happen in the brain. The control model may still be partially timing based, as digits are presented at fixed time intervals, but the working memory input may be switched dynamically based on the output magnitudes of the various associative memories. Table 4 shows a list of action rules that could be used to support such a model. The first rule uses an input signal to recognize when a new number has been presented, and place that number in memory. The second rule serves as a cutoff, as when the decoded output has reached a high level of similarity there is no need to drive the memory until the next number has been presented. The third rule places the result of the addition module in memory if both the most recent and the second most recent numbers are

*Table 3: Action Rules based on Control Signal*

| Control Signal | Utility Calculation | Action |
|---|---|---|
| INPUT for 0.2s | dot(control, INPUT) | memory_input = number_in * position |
| ANSWER for 0.6s | dot(control, ANSWER) | memory_input = addition * answer |
| WAIT for 0.4s | dot(control, WAIT) | memory_input = 0 |

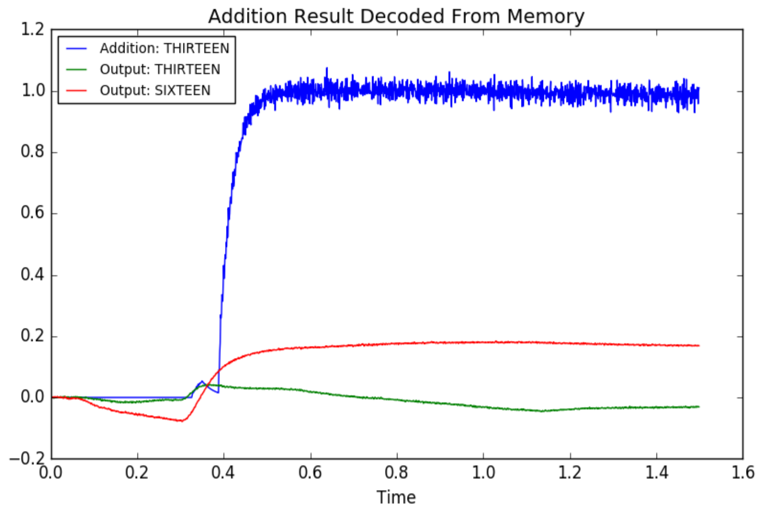


*Figure 6: Output decoding when driving memory with addition result. The desired output is THIRTEEN, but the output does not appear to be affected. The addition result is fed into the memory from t = 0.5s to 1.1s.*

*Table 4: Action Rules for Adaptive Memory Input*

| Utility Calculation | Action |
|---|---|
| dot(control, INPUT) | memory_input = number_in * position |
| output_magnitude | memory_input = 0 |
| one_magnitude + two_magnitude – 1 | memory_input = addition * answer |
| 1.8 – one_magnitude | memory_input = number_in * position |
| 0.9 | memory_input = 0 |

well represented, which means the output of the addition module should be accurate and have a high representation accuracy. The fourth rule acts as a reinforcement, where if the most recent number begins to fade from memory it can be recalled. This rule is based on the assumption that the most recent number may also be recalled from other areas, such as auditory working memory. Finally, the last rule ensures that actions are only taken if there is a high level of confidence in the representation accuracy for the numbers decoded from memory. I was not able to thoroughly test these rules, due to the issues I encountered trying to drive the memory with the addition module ouput.

Once all parts of the model have been put together, the model needs to be run for a sequence of 61 digits to compare the model to human performance. For this test, I removed the connection from addition module to the memory, and only looked at the addition module result. An ISI of 0.8 seconds was used, with the current input number used to drive the working memory for the first 0.2 seconds of each interval. The model was run against a sequence of 31 digits to verify performance over larger spans. Figure 7 shows the output magnitude of the cleanup memories for the most recent number, the second most recent number, and the addition module output.

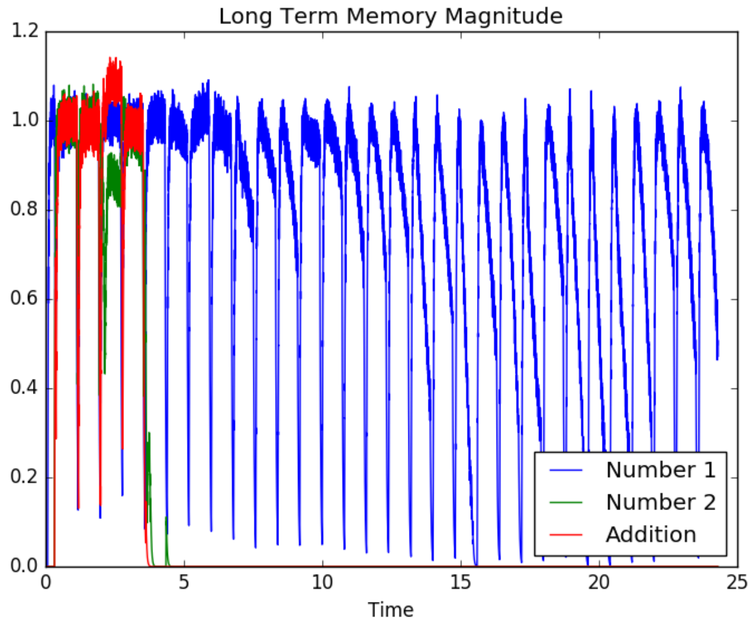


*Figure 7: Long Term Memory Recall. After t = 3.0s the memory begins to rapidly lose held values, leading to complete failure to recall the second most recent number, and a rapidly decaying most recent number.*

The model is able to represent the value of the most recent number, since it is consistently being driven. However, the memory begins to fail after around t = 3.0s. The value of the second most recent number can no longer be recalled, leading to a loss of the addition signal. Additionally, the most recent number begins to decay rapidly, making it unusable as an input to the addition module. I was not able to figure out the cause of the memory failure. The failure does not appear to be directly affected by changes to the recency memory itself, as changes to the number of subdimensions, neurons per dimension, and the feedback synapse still resulted in recall failure beginning around t = 3.0s. I also looked at the input to the cleanup memories (the raw vector decoded from memory), but did not see any obvious reasons for the lack of recall. I think a response suppression memory would improve the recall, but I did not have time to implement one.

I did not have time to explore the effects of a TBI on the model. I briefly explored how to change connection weights for specific parts of the model, but since I did not have a model that approximated the basic functionality of the PASAT I did not think damaging an incorrect model would provide any insights. The damage would have been based on the damage distributions shown in Table 2, with the working memory receiving damage to 44% of its connections and the addition module receiving damage to 40% of its connections. The damage would have been implemented as random changes to the connection weights, and I likely would have experimented with the degree of change to match the expected performance deficits.

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