SHORT TERM MEMORY IN A NETWORK OF SPIKING NEURONS

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A distributed connectionist model of spiking neurons (INFERNET) is used to simulate various aspects of Short Term Memory. In INFERNET, short term memory is the transient activation of long term memory elements. This single store model has a human-like performance in short term memory span tasks, but also displays serial position effects, similarity effects, and double dissociation between short and long term memory which are considered as the main psychological arguments in favor of the multiple-store model.

1 Introduction

Cognitive psychology distinguishes short term memory and long term memory. Short term memory (STM) or Working Memory (WM) refers to the memory trace that is maintained during the human psychological present, and long term memory (LTM) is the storage of past experiences. The separation of LTM and WM into two systems, the idea that information can be loaded from LTM into WM, and that LTM can be constituted by loading the WM content into LTM are the basic ideas of the multiple-store model. In contrast to this multiple-store model, connectionism has often favored a unitary model. This paper will show how a distributed connectionist network of spiking neurons (INFERNET) can exhibit characteristics of WM and LTM without separating them. Networks of spiking neurons have been proven capable of simulating some characteristics of STM like the Sternberg effect [16, 17]. In this paper we further evaluate the ability of a network of spiking neurons to exhibit characteristics of memory.

1.1 Arguments for STM LTM distinction

Some early studies [11, 22] found that in free recall the first items and the last items were better remembered. In free recall, people memorize a series of 10 or 15 or even 40 items (more than the span). The participants' task is to recall as many items as possible, regardless of order. For lists from 10 to 40 items people are better at remembering the first items in the list and even better at recalling the last items of the list. The fact that the last items are recalled better is called the recency effect, while the fact that the first items are recalled better is called the primacy effect. It was showed [26] that if one increases the time between the last presentation of items and the beginning of the recall phase to approximately 15 seconds, the recency effect disappears while the primacy effect remains. The multiple store model explanation is that the first items are stored in LTM, while the last items of the list are stored in STM. Deferring recall has an effect on STM, but no effect on LTM.

The conclusion is that STM must be separate from LTM, since the recency effect is an STM effect. However, one study [5] shows that if one ask rugby players to recall all the teams with whom they played since the beginning of the season. A recency effect appears in this purely LTM task.

The phonological similarity between letters or between words produces replacement errors or impaired immediate serial recall in STM tasks [2]. Semantic similarity, on the other hand, does not produce as many errors. Visual similarity among items has also been found to impair STM [19]. In LTM, it was found [3] that semantic similarity does induce more errors, while phonological similarity does not. The multiple store model proponents conclude that STM and LTM do not use similar coding systems and for this reason must be separated.

Some neuropsychological data indicate a double dissociation between STM and LTM. Some patients have a normal STM and defective LTM [6] while others have a normal LTM and impaired STM [27]. Again, the multiple store model proponents conclude that this supports the conclusion that STM and LTM are separate.

2 INFERNET

INFERNET is a network of spiking neurons [21]. In INFERNET, nodes can be in two different states: they can fire (be on), or they can be at rest (be off). A node fires at a precise moment and transmits activation to other connected nodes with some time course. When a node activation or potential reaches a threshold, it emits a spike. After firing, the potential is reset to some resting value. Inputs charge the node potential, but some part of the node potential is lost at each time step. Spiking neuron models use a quite realistic post synaptic potential function. A complete description of INFERNET can be found in [30, 31].

In INFERNET, a symbol is represented by a cluster of nodes and is activated if its nodes fire in synchrony (the firing distribution must be tightly concentrated around the mean). Different symbols share nodes, so representations are distributed. Attributes are bound to an object and objects are bound to their roles by synchronous firing. There is considerable neurobiological evidence for considering synchrony as a possible binding mechanism in the brain [29]. Discrimination is achieved by successive synchronies. There is evidence [12] to show that if several objects are present in a scene, several groups of cells are clustered in distinct windows of synchrony.

2.1 INFERNET STM capacity

A number of neurobiological parameters are involved in representations that rely on clusters of nodes firing simultaneously. The first is the frequency of oscillation. In INFERNET, once a node is activated, it tends to fire rhythmically between 30 and 100 Hz. The temporal gap between 2 spikes of a node is therefore from 10 to 33 ms. This corresponds to the observed 30-100 Hz (γ wave) oscillations of certain types of neurons. These γ waves have been observed to be associated with attention [34] and with associative memory [36]. The second key parameter is the precision of synchrony. This precision is between 4 to 6 ms [29].

This allows us, as Shastri & Ajjanagadde [28] proposed, to approximate the number of windows of synchrony that could be differentiated, i.e. 25/5 = 5 with a typical 40Hz γ frequency. If we assume that a window of synchrony corresponds to an item or a chunk in STM, then this puts STM span at approximately 5, with a small amount of variance since precision is proportional to oscillation frequency. This corresponds to current estimates of human STM span. It has been argued that the true capacity of STM was actually lower than seven [8, 10, 13, 20, 37]. An item can be a word, an idea, an object in a scene or a chunk, i.e., a grouping of items. Similar explanations for the brain's ability to store approximately 5 short-term memory items can be found in [16, 17, 20, 28, 30, 31, 32].

How can representations be maintained in STM? The problem with γ waves is that they persist only a few hundred milliseconds. This is not long enough to reflect the time taken by people to draw inferences, nor does it correspond to standard estimates of STM retention time (10 to 20 seconds). For this reason, following Lisman [16, 17], γ waves in INFERNET restart every 146 to 333 ms. This corresponds to θ waves [3 - 7 Hz] whose duration can exceed 10 seconds. The resulting temporal firing pattern for a single node is a set of firings at 40 Hz which restarts every ± 300 ms. This is followed by a resting period of approximately 75 ms. Thereafter, the process begins again. There is neurobiological evidence for this rhythm in STM. Θ waves have been observed to be associated with visual short term memory tasks in monkeys [23]. This wave was maintained as long as attention was required.

STM capacity is limited, and chunking increases the amount of information it can contain. In INFERNET, chunking is achieved by two processes. The first is by increasing the number of nodes – and, as a result, increasing the number of objects or symbols firing in synchrony. This is achieved by means of spreading activation. The second is by replacing the content of two or more windows of synchrony by a single one that sums the two windows of synchrony. This is achieved by the use of excitatory and inhibitory connections. Examples of chunking are provided in [30].

We will run simulations on INFERNET to explore STM capacity. In this experiment, 84 nodes fire rhythmically with a delay of 30ms. They are distributed over 30ms to cover the entire interval. This represents the context or task nodes. In the presentation phase, as input, each object node will only fire twice per theta cycle and will respect a particular sequence (see Figure 1). "Object 1" nodes will fire twice, then "Object 2" will fire twice etc. The phase assigned to each object is randomly chosen. In the presentation phase, object nodes will fire at the same time as particular context nodes, thereby binding the object nodes to the associated context nodes. The connections linking context and object nodes will be modified. In the test phase, context nodes will fire and the simulator memory will be evaluated by looking at the firing of object nodes.

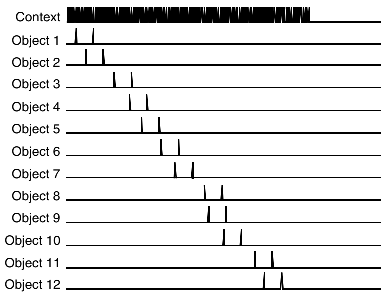

Figure 1: An example of input for the binding- learning phase for 12 objects. The particular phase is randomly assigned for each object.

In this experiment, there were 7 nodes per object, and objects inhibit each other (inhibitory connections with a delay of 30ms). There is a probability for noise on the delay, and therefore the nodes will not always fire precisely at 30 ms intervals. The more windows of synchrony that are required, the more competition there will be among nodes, since there is an increased probability that 2 nodes pertaining to different objects will fire in synchrony. In that case, we would expect that the proportion of recall will decrease as a function of the number of items to memorize. This is, in fact what happens. Figure 2a displays the proportion of correct recall for different list lengths. Twenty trials for 4, 5, 6, 7, 8, 9, 10, and 12 items were tested with the INFERNET simulator. Normalized correlation was computed for each object node firing time. This is a correlation between data observed and data that we would obtain for perfect recall. We are looking only for cases in which all items are recalled in the correct order. In a span task, if one item is missing, the response is considered incorrect, therefore correlations obtained for all objects were multiplied. In order to compare these results with human data, we plotted data from various studies in which the authors collected the frequencies of correct recall for different list lengths without stopping the experiment after the first error.

Data reported in Figure 2a show a decrease of correct recall as the number of item increases. Moreover, the decreasing function is sigmoidal in shape. INFERNET seems to be somewhat better than humans, but the important point is that STM capacity is limited and that the decreasing functions are parallel.

1.2 Forgetting

Forgetting in INFERNET is caused by both trace decay and interference. Connections that were strengthened during a presentation phase, will decay slowly over time. This is compatible with a trace decay. When there are many objects to be distinguished, competition for windows of synchrony increases and, as we showed in the previous section, the proportion of correct recall decreases. This is compatible with what would be produced by interference. The data presented in the next section are a result of these two processes, i.e. decay and interference.

1.3 Serial effects

What happens when INFERNET has to memorize a number of items beyond its span? The following simulation examined which items were recalled. Forty networks were tested with the task of memorizing 12 items. The procedure was the same as the preceding simulation. For each item, the proportion of recall was computed. The results are shown in Figure 2b. We also report typical human data.

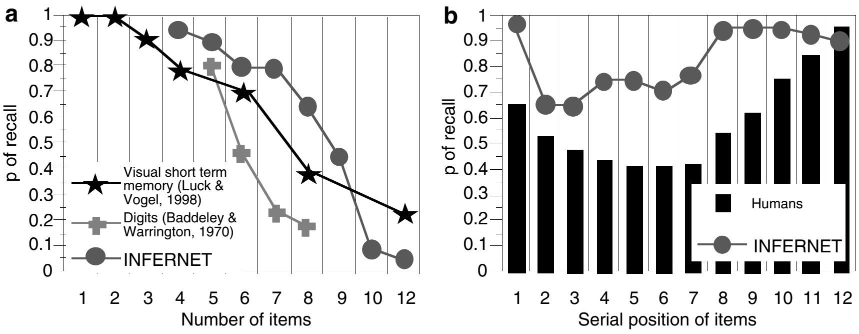

Figure 2a: INFERNET and human short term memory capacity (20 networks tested); b: INFERNET serial position effect

As we see, the first item in INFERNET is recalled better than successive ones. The five last items are also recalled better. INFERNET displays a primacy and a recency effect without separating LTM from STM. The primacy effect is caused by interference, and the recency effect by trace decay. In Figure 1, we plotted the input that is provided to INFERNET in the presentation phase with 12 items. Each object node is externally excited twice, but these nodes will continue to oscillate independently at the γ frequency. The only object nodes that are not in competition with others are the nodes associated with the object that was presented first. The others will always be presented when other object nodes are already oscillating. This is why the object presented first is recalled better than subsequent ones. In the presentation phase, learning happens when independent excitation is synchronous with external excitation. For the objects presented first, at the end of a γ cycle, the time elapsed from this moment will be longer than for the items presented last. If the nodes associated with an object continue to oscillate, nothing will happen, but if a node stops oscillating, the connection strength from the bound context nodes will decrease. The more time that has elapsed from external excitation, the more the chance of having a node that stops firing. That is why the items presented first have a greater chance that their connections from context nodes will decay.

The data reported in Figure 2b shows that INFERNET performs better than humans, and that the INFERNET trace decay takes more time. Nevertheless, both primacy and recency effects occur with a unique system for STM and LTM. It should be possible to obtain a better match with different settings of INFERNET parameters.

1.4 Similarity

The following simulation will show how INFERNET reacts when the objects to memorize are similar. The similarity between objects was simulated by assigning to the different objects a common node. Five objects were created. Each contained 7 nodes. In the dissimilar group, the 5 objects were represented by 7 different nodes; for the similar group, the five objects had 6 of their own nodes and one common node (i.e. a degree of similarity of 1/7). The frequency of correct recall was computed as before. Data were collected on 40 networks for each condition. The results are displayed in Figure 3a, and are compared with Baddeley data [2], Experiment 1.

The INFERNET results show an effect of similarity between items. The slope of the decreasing function falls between the effect of acoustic similarity and semantic similarity. The important point is the existence of a similarity effect. The number of nodes shared by objects could have been increased in order to obtain an effect similar to that observed for "acoustic similarity".

1.5 Double dissociation between LTM and STM

In this simulation, the ability of INFERNET to display double dissociations between STM and LTM was explored. Three settings were tested with 20 trials per settings. The STM was tested as before, noting the proportion of correct recall for a list of 5 objects. An LTM was included in the system: each of the 5 objects were linked with a particular object. The experiment involved 10 objects. This simulation can be viewed as if the network were maintaining a list of exemplar words like robin, siamese, begle, trout, oak in STM and the LTM task involved correctly associating each word with a particular category: robin-bird, siamese-cat, beagle-dog, trout-fish, oak-tree. Specifically, the LTM score is the total number of category node firings divided by the total exemplar node firings. If the category is well represented in LTM, whenever an exemplar is activated, the corresponding category will be activated.

For the first group ("Normal") the noise on delay probability was set low and the links between our five exemplar-category pairs were maintained. For the impaired LTM group, the noise on delay probability was maintained low but 5/6 of the links between exemplars and category were destroyed. For the impaired STM group the noise on delay probability was raised and the content of LTM was the same as in the "Normal" group.

The INFERNET results are displayed in Figure 3b. These data clearly show a double dissociation between STM and LTM. Other variables could also have been used to obtain this double dissociation. Noise decreasing connection strength should affect more LTM than STM, binding-learning rate should afflict more STM than LTM, etc. This experiment illustrates the fact that in order to obtain double dissociations two variables alone are sufficient.

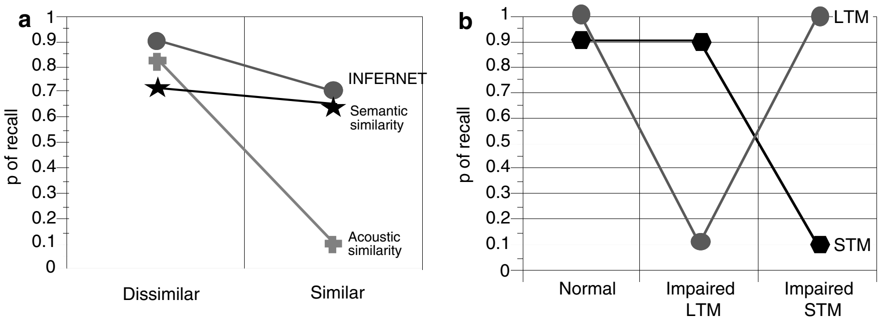

Figure 3a: Effect of item similarity on STM performance; b: INFERNET simulator results on double dissociation between LTM and STM (20 networks).

3 Discussion

Considerable data have been collected in the last half century on memory. A number of phenomena have been discovered and assessed. Our goal was simply to review a number of classic phenomena and to test INFERNET to see the extent to which it can account for them. The overall picture that INFERNET draws is quite close to reality. This agreement is especially interesting as INFERNET (a single-store model) simulates data that are considered by many authors to be the main arguments for the multi-store model. Supporters of the multi-store model could always argue that even if STM is the activated part of LTM, STM is nonetheless functionally distinct from LTM in INFERNET. But since LTM and STM both share the same substrate, they are *not* functionally independent in INFERNET. This is important in explaining data involving the relationship between LTM and STM. For example, one study [15] showed that the STM span is higher for words than for non-words (which have no semantic representation in LTM). Memory span is worse for foreign language words than for mother-tongue words [15]. Experts have a better STM than novices [9]. High frequency words are better remembered than low frequency words [35]. To explain these data, some [18] proposed that information in working memory also activates LTM traces. But the results from INFERNET, a single-store model, suggest that dual STM-LTM systems are probably unnecessary.

The contribution of INFERNET over "box" models [1, 4] is the level of processing details. These "box" models provide a gross description of phenomena.

Consequently, one would have great difficulty building a computational model based on these descriptions without building in a large number of special purpose mechanisms. For example, in Baddeley's model, the phonological loop is responsible for maintaining verbal information. What are the mechanisms of looping, why does it start, why does it stop? Why is the phonological store impaired by phonological similarity? Many processes have been attributed to the central executive ensuring the model fits empirical data, but nothing is said about how this central executive actually works. Some researchers even doubt its very existence [25].

INFERNET does not separate objects, symbols, and phonemes and, as a result cannot model effects related to different codings involving word-length effects, semantic vs. phonemic similarity, and speech rate effects. However, such distinctions could likely be done as extensions of the present INFERNET architecture. Some connectionist work has already been done on this subject [14].

Some other connectionist models [7] simulated STM span and similarity effects but did not succeed in simulating serial effects. Others [24] simulated similarity effects, but with modifying the activation of item nodes according to their similarity. Serial effects also have been obtained [24] but the activation strength of item nodes were decreased externally according to their position in the list.

We [32] provided a theorical explanation of the Sternberg memory scan effect [33] within the framework of INFERNET model. The memory matching capabilities necessary to do this task have not yet been implemented in INFERNET. Others [16, 17] provide an elegant explanation and simulation data on this problem with a model very similar to INFERNET. The difference lies in the fact that the different items are encoded in different phases inside a theta cycle instead of gamma cycle in INFERNET.

INFERNET is a theoretical and computational model that gives detailed and falsifiable predictions, and provides detailed mechanisms of cognitive phenomena grounded in neurobiology. Its limits in explaining certain data also provide perspectives for future work.

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