Reconciling two computational models of working memory in aging

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Abstract

It is well known that working memory performance changes with age. Two recent computational models of working memory, TBRS* and SOB-CS, corresponding to two distinct causes of forgetting, namely time-based decay and interference, are applied on a set of complex span data produced by young and older adults. As expected, these models are unable to account for the older adult data. An investigation on the effect of the main parameters of these models showed that the poorer performance of older adult does not come from a weaker encoding of items, or even a longer time spent on distractors, but rather on difficulties during the free time that immediately follows each distractor, as well as a higher level of confusion between items. These results are discussed with respect to the current theories of working memory and aging.

Keywords: working memory; aging; TBRS; SOB-CS.

Introduction

Working memory is a cognitive construct that describes how information can be maintained for a limited period of time, while concurrent processing is also performed. Several computational models of working memory have been proposed in the last decades. Most of them concern young adults. However, it is known that working memory tends to decline with age (Logie & Morris, 2004) for reasons that are not completely understood. Indeed, several explanations have been proposed and the question is still under debate. This paper is an attempt to contribute to the debate by means of a computational modeling approach.

To this end, we will test two recent theoretical models that propose two distinct mechanisms to account for forgetting in working memory: time-based decay and interference. Despite a strong opposition between these two models in the recent literature, we will show that adapting each one to reproduce older adult data leads to similar conclusions about the reason of the older adult working memory loss of performance.

The first model, named TBRS for Time-Based Resource Sharing (Barrouillet, Portrat & Camos, 2011) claims that our difficulty to maintain several items in memory while performing distracting tasks in-between their presentation comes from the fact that item activation decays with time as soon as attention is directed towards another item or a distractor. Hence, according to TBRS, working memory performance depends on the cognitive load of the processing task, which is defined as the proportion of time during which this task captures attention. This model is supported by several experiments using a complex span design (e.g. Barrouillet, Bernardin, Portrat, Vergauwe, & Camos, 2007; Portrat, Barrouillet, Camos, 2008; Vergauwe, Barrouillet, & Camos, 2010).

The second model, called SOB-CS for Serial Order in a Box – Complex Span (Oberauer & Lewandowsky, 2012), has a completely different point of view. It is based on the idea that forgetting is not based on decay but rather on the effect of interference between items or between items and distractors. The interference from distractors depends on the strength of their encoding and this strength relies on the novelty of the to-be-processed items. This novelty varies with the number of to-be-processed items and their similarity: the more the number of items, the poorer the recall and the more similar the items, the better the recall performance.

There has been a strong debate in the literature in the past years between these two models (Plancher & Barrouillet, 2013; Lewandowsky, Geiger, Morrel, & Oberauer, 2010). It is therefore useful to challenge both models by testing how they would account for older people data, in particular because older people present reduce attentional capacities (Luo & Craik, 2008) but are also more sensitive to interference (Hasher, Zacks, & May, 1999). We therefore first present the data that we collected on a complex span task on young and older people.

Experiment

Procedure and Material

In a serial recall task, participants were presented with 5 images in-between which they had to read aloud 3 distractor words. They were then asked to recall the image names in order. Such a trial was repeated 16 times. In order to study both a possible interference effect and a time effect which are markers of SOB-CS and TBRS respectively, we defined two variables:

- the novelty of distractors which either contain repetitions (low interference, e.g., *duck, duck, duck* or *duck, duck, horse*) or all distinct (high interference, e.g., *duck, plane, horse*);

- the duration in-between distractors, which could be long (slow pace, one word to read every 2 seconds) or short (fast pace, one word to read every 1.2 seconds).

There were therefore 4 experimental conditions resulting from two types of novelty of the distractors (repeated vs. novel words) and two paces of the processing task (fast vs. slow), with then four trials in each condition. Repeated distractors are generally three identical words (AAA), but we also used patterns in which only two are identical and the third one different (called ABA, ABB or AAB), in order to prevent participants from anticipating the distractor.

Participants

20 young participants (12 females; mean age = 21.62; SD = 2.51) and 20 healthy older participants (13 females; mean age = 71.92; SD = 5.18) voluntarily took part in this experiment.

Results

As expected, the two populations behave differently. Older participants recalled fewer images (2.80) than younger participants (3.78), F(1,38)=27.77, p<.001. An interesting finding is that older adults did not spend more time to process distractors (489 ms in average) compared to young adults (527 ms). Their worse recall performance therefore does not come from a longer time spent on distractors.

We now present two sets of simulations performed on two computational models that are able to simulate a working memory trial, TBRS* and SOB-CS. Each model is exposed to 5 items during 1500 ms each. In-between each presentation of items, three distractors are presented during a specific duration that corresponds to the time actually spent by participants for reading a distractor word. Models then simulates the recall phase at the end of each trial. When asked to recall an item at a given position, models could, exactly like participants, recall the correct item, recall a wrong one or even do not recall anything if none of them is activated enough in memory.

TBRS*

Description

TBRS* (Oberauer & Lewandowsky, 2011) implements the verbal theory (Barrouillet et al., 2011) which assumes that the core component of working memory is attention. If attention is directed towards an item, its activation value is increased and the activation values of all other items is decreased. TBRS* is based on a two-layer connectionist network. One layer is composed of nodes representing the items to be memorized and the other layer encodes the sequential position of items. Each position is coded by a subset of position units, so that two adjacent positions share a proportion of P units. Memorizing is modeled as a process of connecting positions with items, by Hebbian learning (Anderson, 1995). The strength of the increase of any connection weight (w) depends on a strength value (η) and it is bound by an asymptote L, defined in such a way that the total activation strength of an item is always between 0 and 1: $\Delta w = (L - w)\eta$. The strength depends on the time t devoted to encoding as well as a stochastic parameter r modeling human variability: $\eta = 1 - e^{-r.t}$ with $r = \mathcal{N}(R, s_2)$.

For instance, if the sequence of letters to be memorized is KZFP, K is first encoded which results in strengthening the links between item K and the nodes coding for position 1. When attention is captured by another task, like reading a word in our case, those values w decrease according to an exponential function: $w(t) = w_0.e^{-D.t}$.

When attention is redirected towards the memory task, a refreshing process takes place and leads to an increase of the w values. All positions are successively considered, starting with the first one, and the most activated item at each position is retrieved and refreshed. In order to simulate retrieval errors, a Gaussian random noise, defined by its standard deviation , is added to each item node before the best one is selected.

This refreshing process cycles until a new activity requires attention.

To pursue our example, when Z is encoded, activation values between the node representing Z and the node representing position 2 are strengthened (while in the meantime, the activation values of K are decreased). If there is time for refreshing, it is alternately done between the items retrieved at position 1 (K if there is no retrieval error) and the one at position 2 (Z in most cases).

Comparison to experimental data

TBRS* was run[1] 5 000 times on each experimental condition (slow or fast pace repeated or unrepeated distractors) for young and older adults, using the default parameters suggested by Oberauer & Lewandowsky (2011). Since TBRS* does not model interference between distractors, the experiment was simulated by computing the durations of processing distractors according to the different patterns of repetition discussed previously: AAA, ABA, ABB, AAB and ABC. The only difference between young and older adult simulations comes from the variability of the time used by participants to process a distractor, as mentioned previously. Results are presented in Table 1.

As expected, it turned out that the model reproduces quite well the young adult performance but it cannot account for the older adult data.

Several TBRS* parameters could be tuned to better reproduce the lowest performance of older adults, representing thus possible causes of forgetting in WM. We investigated the effects of the level of noise (σ) which controls the amount of retrieval errors, the decay rate (D), the encoding strength (R) and the duration for refreshing an item in the refreshing cycle (T_r). We performed a grid search in this 4-dimensional space and computed for each point the root mean square error (RMSE) between each model score under the 4 conditions and the averaged experimental data. We then studied the effect of each parameter by performing a projection on the parameter dimension, and analyzing the evolution of the

[1] data and model codes that have been used in this work are available on the first author webpage

Table 1: Mean number of items recalled in each condition, for young and older adults (observed/Data and simulated/TBRS* and SOB-CS). Both models used default parameters.

FAST PACE

	Low Interference		High Interference	
	Young	Older	Young	Older
Data	3.51	2.55	3.69	2.88
TBRS*	3.51	3.52	4.33	4.32
SOB-CS	3.64	3.67	3.57	3.59

SLOW PACE

	Low Interference		High Interference	
	Young	Older	Young	Older
Data	3.90	3.04	4.03	2.73
TBRS*	4.19	4.18	4.43	4.40
SOB-CS	3.98	3.99	3.97	3.99

average RMSE.

Figure 1 and 2 show the average RMSE as a function of various values for the noise σ and he duration of atomic refreshing T_r, for both young and older adults.

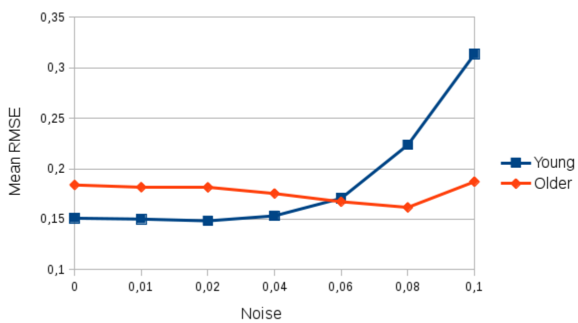

Figure 1: RMSE between TBRS* simulation and data as a function of the noise parameter σ.

It turned out that the models better fit the older adult data for a higher level of noise (0.08) compared to the young adult data for which the best RMSE is for a low level of noise, coherent with the default value of 0.02 proposed by Oberauer & Lewandowsky (2011) for young adults. The higher that noise, the more likely retrieval errors. This could be the sign of a weaker inhibition ability for the older population or a higher sensitivity to interference.

The duration for refreshing a single item during free time, in the refreshing loop, also needs to be adjusted to reproduce the older adult data. That parameter was set to an average value of 80 ms in the original model, which, for instance, permits to make a full cycle of refreshing the five items in about 400 ms.

The best RMSE for young adults is now obtained for a value of 40ms, half the default value of the original model

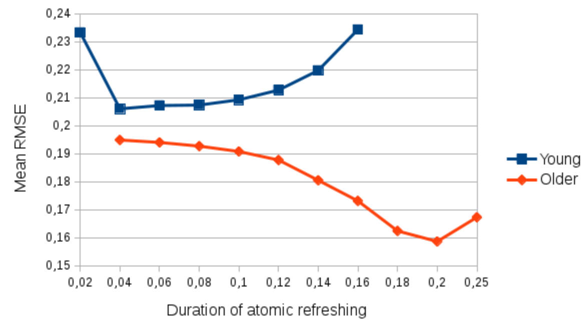

Figure 2: RMSE between TBRS* simulation and data as a function of the duration of atomic refreshing T_r.

but coherent with Portrat & Lemaire (in press) which showed that this value has to be decreased if the model has an attentional focus size of only one item at a time. As expected, the best RMSE based on the older adult data is obtained for a much higher value of about 200 ms for refreshing a single item, which is 5 times the duration of the young adult model.

However, we could not find any difference between young and older people concerning the rate of encoding strength, nor a significant difference between decay rates.

To summarize, two parameters need to be adjusted to fit older adult performance. First, the noise during retrieval for refreshing or recall has to be increased. Second, the duration for refreshing a single item during the free time available in-between processing steps has also to be substantially enlarged.

One interesting finding of that simulation is therefore that the older population would not suffer from a lack of encoding, but rather from difficulties in taking advantage of the free time that occurs after each distractor, either because of inhibition difficulties or defaults in managing interference (parameter σ) or because it takes time for them to refresh items (parameter T_r). We now present the second model that we used to simulate our data .

SOB-CS

Description

SOB-CS (Oberauer & Lewandowsky, 2012) assumes that working memory limitation is due to interference between to-be-maintained items or between items and distractors. This model is also based on a two-layer connectionist network that associates a distributed item representation with distributed position markers. Contrary to TBRS*, item representation is distributed in order to reproduce interference between items, distractors and both according to their similarity. For instance, if items are highly similar they share patterns across the same set of units, and inversely, different items are represented with very different patterns.

Memory is maintained by standard Hebbian learning (Anderson, 1995): $\Delta W = \eta_e(i).W$ where $W = v_i p_i^T$ represents the weight matrix connecting the ith position markers p_i with

ith item representation v_i and $\eta_e(i)$ represents the encoding strength which depends on the time spent to encode (t_e), the rate of encoding R and the item's novelty $A(i)$ by means of $\eta_e(i) = A(i)(1 - e^{-t_e.r})$. Item's novelty reflects the degree of mismatch between the expectation (computed as $W.p_i$) and the actual item. The higher the novelty, the stronger the encoding.

SOB-CS assumes that, during the processing step, distractors are encoded in the same way as items such as $\Delta W = \eta_e(i,k).d_{i,k}.p_i^T$ where $d_{i,k}$ represents the distractor k following item i and $\eta_e(i,k)$ is the encoding strength of the distractor. That is the reason why a distractor following item i creates interference on this item. Because of the item's novelty notion, repeatedly processing the same distractors produces less interference than does processing different distractors.

After each processing step, more or less free time is available which allows restoration of an unimpaired memory state. The removal of the distractor has been modeled by Hebbian antilearning : $\Delta W = -\eta_r(i,k).d_{i,k}.p_i^T$ where $\eta_r(i,k)$ is the antilearning strength which depends on the free time t_f, the rate of removal r of representations from working memory and the asymptotic value $\Omega(i,k)$.

Finally, for the recall step, the position markers are used as cues to determine which items to recall. For instance, to recall the ith item, the vector position p_i is considered to compute $v_i' = W.p_i$, which is the distorded version of the original vector v_i. To retrieve this original item v_i within all the candidates item of the list, the model computes all the probabilities of recalling an item j depending on the similarities $s(v_i', v_j) = e^{-c.D(v_i',v_j)^2}$ with c, the discriminability parameter and D the euclidian distance between v_i' and v_j. Before each recall item, a Gaussian noise with a standard deviation N_o is added to represent output interference.

Comparison to experimental data

As previously described for the TBRS* simulation, we first simulated the young and older adult data, with the default parameters suggested by Oberauer & Lewandowsky (2012), using also 5000 runs for each condition. As in TBRS*, the difference between young and older adult simulation comes from the variability of the time used by participants to process a distractor. However, contrary to TBRS*, the fact that distractors are repeated or not in the experiment is taken into account by SOB-CS. Results are presented in Table 1. Like TBRS*, SOB-CS reproduces more accurately the young adult performance than the older adult one.

Hence, we studied the effect of four parameters proper to this model to better fit the performance of older adult: the encoding rate (R), the removal rate (r), the standard deviation (N_o) of the Gaussian noise added to each weight in W after recall of each item and the discriminability (c) between recall candidates which controls the level of confusion between retrieval candidates.

Figures 3, 4 and 5 show the average RMSE as a function of the various values for the removal rate (r), the discriminability (c) between recall candidates and the standard deviation N_o of Gaussian noise respectively for both young and older adults. The model better fits the older adult data for a lower discriminability (0.9) compared to young adult data for which the optimal RMSE value appears to be much higher, even higher than the default value (1.3) proposed by Oberauer & Lewandowsky (2012). With lower values of c, similarity falls off less steeply with distance, so that the most similar candidate is less clearly discriminated from the less similar ones. In accordance with a decline in inhibition with aging (Hasher & Zacks, 1988 ; Hasher, Zacks, & May, 1999), this lower discriminability for old people could explain more intrusion errors that have been found in the recall of older participants (e.g. Carretti, Cornoldi, De Beni, & Palladino, 2004 ; Hedden, & Park, 2001).

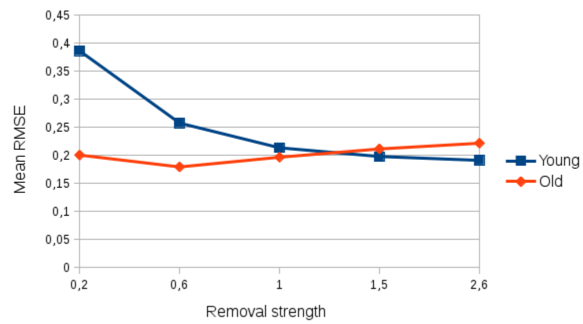

Figure 3: RMSE between SOB-CS simulation and data as a function of the removal rate strength r.

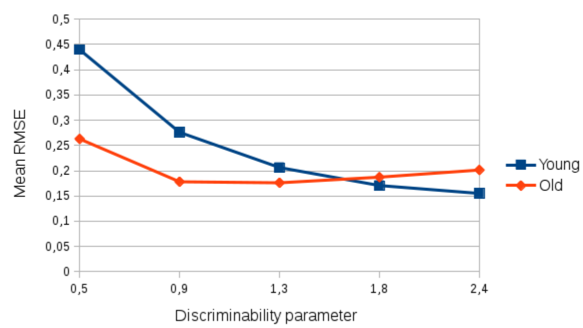

Figure 4: RMSE between SOB-CS simulation and data as a function of the discriminability parameter c.

We also observed that the model simulating older adults needs more time to remove the previous distractor during the free time period than the one based on young adults. The RMSE based on the older adult data is lower for a removal rate (r) of 0.6 whereas the RMSE based on the young adult data is lower for a higher removal rate (1.5 or more), coherent with the default value proposed by Oberauer & Lewandowsky (2012) for young adults. This result is also in line with the inhibition explanation of working memory aging (e.g., Hasher

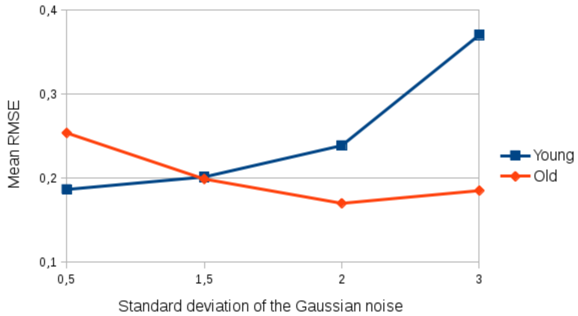

Figure 5: RMSE between SOB-CS simulation and data as a function of standard deviation N_o of the Gaussian noise.

& Zacks, 1988). Older participants would have difficulties to suppress irrelevant information in WM.

The output noise parameter N_o in SOB-CS, which occurs only in the recall step, has also to be modified for a good simulation of the older people performance. Increasing the noise is therefore a good way to simulate older people data.

Finally, as with TBRS*, we could not find any difference between young and older people concerning the rate of encoding strength. An important finding of that second simulation is that the conclusion is exactly the same as with TBRS* simulation: older population would not suffer from a lack of encoding, but rather from difficulties in taking advantage of the free time that occurs after each distractor, either because of inhibition difficulties or defaults in managing interference (parameter c and N_o) or because it takes time for them to remove distractors (parameter r).

Discussion

The aim of the present paper is to give more understanding of working memory aging through the comparison of behavioral data collected on young and old adult with simulations from two very recent and influential models of working memory. The first outcome is that they produced results that are coherent with each other, in spite of their very different theoretical foundations. First, it appears that the strength with which items are encoded does not have to be weaker for the models simulating older adult performance. We could not find any difference between young and older adults for the R parameter in TBRS*. That is exactly the same for the encoding parameter in SOB-CS. This finding tends to indicate that the lower recall performance of older adults would not be due to a lack of encoding the to-be-recalled items. However, the difference between young and older adult performance can be explained by two kinds of parameters, both controlling what is happening during the free time following the processing of each distractor or during recall. The first parameters control the likelihood of confusion between items when retrieving one at a given position whereas the second ones controls the post-distractor processes. In addition, we computed the AIC for both models using the probability mass functions of recalling x items, generated from a binomial model. We found that the two original models do not differ much: on young adult data, $AIC_{TBRS} = 199.03$ and $AIC_{SOB-CS} = 196.02$; on older adult data, $AIC_{TBRS} = 318.74$ and $AIC_{SOB-CS} = 310.57$.

Defaults in the retrieval processes

In the TBRS* simulations, a much higher noise during refreshing and recall has to be set to account for the older adult data. That Gaussian noise, which directly boosts confusion between items, is added to the activation value of each candidate item, each time the model has to retrieve an item before refreshing it or recalling it. The processes in charge of the retrieval of items given a position seems therefore to be affected for the older adults.

A similar result was obtained from the SOB-CS simulations. The parameter controlling discriminability between items has to be decreased to account for the older adult data. A low discriminability produced retrieval errors because the best candidate can be mixed up with other candidates. This parameter is highly similar to the noise parameter in TBRS* because a higher noise added to the activation values of candidate items also introduces some confusion between items.

Defaults in the post-distractor processes

The other kind of parameters that has to be changed in the simulations of older adult data concerns the processes that appear right after processing a distractor. In the TBRS* simulations, to simulate older adults data, the model has to spend 5 times more time to refresh a single item than the default value. It could be that older people needs more time to refresh items but it could also be that they spend time to switch from processing distractor to maintaining items.

This result is in line with what has to be modified in SOB-CS, that is the parameter that controls the removal of the previous distractor, in order to reinstate the correct state of memory. Once again, this process occurs right after a distractor has been presented. According to the results of both model simulations, it is therefore right after the processing phase, when participants have to switch from a distracting activity to a process trying to maintain items vivid in memory, that something goes amiss in older adults.

Theoretical explanations

There are several theories in the literature to explain the lower working memory performance of older people. In this section, we focus on three theories. One strong explanation comes from a deficit of inhibition control (Hasher & Zacks, 1988; Hasher, Zacks, & May, 1999). Older participants would have difficulties to suppress irrelevant information in WM and, in consequence, access to relevant information would be reduced. Our simulations are coherent with that explanation because the processes that have to be altered in the computational models to account for older adult data are precisely those at the frontier between processing a distractor and taking advantage of the free time. And this moment is when an inhibition process occurs.

Another explanation that is proposed in the literature (Salthouse, 1996) suggests that aging goes along with a slower processing speed. The encoding phases of the two models do not have to be modified to account for the data, but we cannot conclude that older people spend as much time as young people to encode items because of the experimental design: duration presentation is probably too long (1.5s) to observe differences of strength encoding at the end of the encoding phases.

Finally, another hypothesis is linked to the deficit of switching between storage and processing. According to Verhaeghen and colleagues (Vaughan, Basak, Hartman, & Verhaeghen, 2008), focus-switching might be a good candidate for the locus of age differences in WM. In accordance, difficulties to remove distractors (SOB-CS) or to refresh items (TBRS*) for older adults could be viewed as a symptom of a longer switching mechanism between processing and storage instead of a deficit of inhibition. Similarly, a higher rate of confusion between items could be the sign of lower accuracy of the process of switching items in and out of the focus of attention (Verhaeghen & Basak, 2005).

TBRS* and SOB-CS are concurrent models simulating working memory in different ways. The present study does not aim at choosing the best of them. On the contrary, we take advantage of both of them to investigate the possible causes for the decline of working memory performance in aging. We found that, in spite of theoretical divergences between these two models, simulations tend to the same conclusions: older people seems to have difficulties of taking advantage of the free time and more confusion between items. It would therefore be interesting in the future to model more precisely that specific moment where the default seems to occur, which is the switching between processing and storage.

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