# No Evidence for Feature Overwriting in Visual Working Memory

Elisabeth Jünger[ab], Reinhold Kliegl[a] & Klaus Oberauer[c]

University of Potsdam[a], University Hospital at Technische Universität Dresden[b] & University of Zurich[c]

Short title: Interference in Visual Working Memory

Address for correspondence: Elisabeth Jünger

Technische Universität Dresden

University Hospital Carl Gustav Carus

Department of Psychiatry and Psychotherapy

Fetscherstraße 74

01307 Dresden

Email: elisabeth.juenger@uniklinikum-dresden.de

Phone: 0049 351 458 2472, Fax: 0049 351 458 5881

## Abstract

The effect of repeating features in a short-term memory task was tested in three experiments. Experiments 1 and 2 used a recognition paradigm. Participants encoded four serially presented objects and then decided whether a probe matched one of them with regard to all three features. In the control condition, no feature was repeated; in the experimental condition features were repeated in two memory objects. Experiment 3 used a cued recall paradigm with the same list design. After list presentation one feature was used as a cue uniquely indicating one of the memory objects. Participants recalled the remaining two features of the probed object. Feature overwriting as one component of the interference model of Oberauer and Kliegl (2006) predicts worse performance in the experimental compared to the control condition. Results of all three experiments did not support this hypothesis. Recognition performances in Experiments 1 and 2 were not impaired by repeating features. Recall performance in Experiment 3 was better for repeated features, contrary to the predictions of feature overwriting. Predictions from feature overwriting for the shape of serial position curves were also not confirmed.

*Keywords:* feature overwriting, interference, visual working memory, recognition, cued recall

**Acknowledgement**

This research was supported by DFG Grant KL 955/6.1. We thank Petra Schienmann for research assistance. Data and R scripts for these experiments are available at the Potsdam Mind Research Repository (PMR2; http://read.psych.uni-potsdam.de ).

## Introduction

Currently, several possible explanations for the limited capacity of working memory are discussed (see Oberauer & Kliegl, 2001 for an overview). One of them is interference (Wickelgren, 1965; Nairne, Neath, & Serra, 1997; Nairne, 2002; Oberauer & Kliegl 2001, 2006; Oberauer & Lewandowsky, 2008). In interference models, capacity limits of working memory result from mutual impairment of simultaneously activated memory representations. One possible form of interference is *feature overwriting*. Feature overwriting is assumed to occur when objects held in working memory share some of their features (Nairne, 1990; Oberauer & Kliegl, 2001; 2006).

Lange and Oberauer (2005) found evidence for feature overwriting in verbal working memory. Participants encoded lists of three-letter nonwords or words. Each memory list was followed by distractors consisting of further nonwords or words, respectively. All items of the memory list and all distractors had to be read aloud. Distractors shared phonological features with one target item in the memory list. Target items were recalled less well than other items. A classical explanation for that finding in the verbal domain would have been similarity-based confusion. Order errors, reflecting confusions between list items, are frequent in serial recall and increase when list items are more similar to each other (Fallon, Groves, & Tehan, 1999). However, in the experiments of Oberauer and Lange (2005), pairwise similarity between each distractor and the target was low. Therefore similarity-based confusion could not easily explain the results, and effects were attributed to feature overwriting. To further rule out similarity-based confusion as an alternative explanation, two additional experiments with verbal material were conducted (Oberauer & Lange, 2008). In one of them participants read aloud four words followed by four consonants. Afterwards, participants were asked to recall the complete list. One word had phonemes in common with three of the four consonants and should suffer from feature overwriting. For example the word “fond” should be overwritten by the letters “N” “D” and “F”. Again, target words for feature overwriting were recalled less well than other words. Because letters were never confused with words, similarity-based confusion could not explain the results.

Oberauer and Kliegl's (2006) interference model provides an explanation for feature overwriting. The model conceptualizes features in analogy to neuronal units that can be bound to only one specific object at a particular time. The model builds on the idea of temporal phase synchronization as a binding mechanism in working memory (see Fell & Axmacher, 2011; Feldman, 2013, for reviews). The theoretical framework of phase synchronization is based on neurons that can be rhythmically activated and inhibited. Temporal phase synchronization establishes associations between feature coding neurons of a stimulus and different brain regions (Fell & Axmacher, 2011). Temporal phase synchronization in Oberauer and Kliegl's (2006) model works as follows: neurons coding features belonging to one object fire in synchrony with each other, whereas neurons coding features belonging to different objects fire out of sync. If two or more objects share one feature, each feature coding neuron can synchronize its firing with only one object. Assuming that there is a limited pool of neurons coding the same feature, this implies that the shared feature is reduced in strength for each object, or lost for some objects entirely. This process is called feature overwriting. If a feature is coded by only one unit, binding that unit to an object implies that the feature cannot be bound to any other object at the same time. Thus, in principle, if the feature red is coded by a single unit, subjects who encode two red figures into working memory should only remember one red figure afterwards. If a feature is coded by several redundant units, then units coding the repeated feature would have to be shared between objects, and repeated features would be bound to each object with reduced strength. For instance, if 100 units code red, then two red figures would be represented in working memory, but their color would each be coded by only 50 units, on average. Either way, the memory representations of repeated features would be impaired in some or all objects with that feature.

To summarize, feature overwriting in the model of Oberauer and Kliegl (2001, 2006) is the process of binding specific feature coding units to only one object at a given time, to the detriment of other objects sharing the feature. Here we report three experiments designed to test feature overwriting as described in the model of Oberauer and Kliegl (2001, 2006) in visual working memory. To foreshadow the results, we obtained no evidence for feature overwriting in our visual working memory tasks.

## EXPERIMENT 1

We used a recognition paradigm with objects consisting of three features: *shape*, *texture*, and *color*. In the control condition no feature was presented twice within a list. In the experimental condition one shape, one texture, and one color were presented in two objects.

### Method

#### Participants

We tested 34 people, 18 of them female, aged between 16 and 28 with a mean of 20.9 and a standard deviation of 3.6 years. Most of them were students from the University of Potsdam. For their attendance in the experiment, which took about 45 minutes, they received 6€ or credits for participation. All participants had normal or corrected-to-normal vision and none of them were color blind.

#### Apparatus

The experiment was conducted using *Apple Macintosh Performa 6300* computers. The paradigm was programmed in *MATLAB* and based on the operating system *Mac OS 8.0*. Two 17 inch flat screen monitors were used, with a resolution of 1024 x 768 pixels and a rate of 75Hz. Participants made their responses by pressing the right and left arrow keys.

#### Stimuli

Memory objects of Lange and Oberauer (2005), and Oberauer and Lange (2008) were nonwords consisting of three letters, or short words. We used memory objects that also consisted of three features: *shape*, *texture*, and *color*. An object could be, for example, a square with red stripes. The 216 possible items, each with three feature dimensions, were derived from the factorial combination of six shapes, six textures, and six colors. The shapes and textures are shown in Figure 1. The six colors were *black, red, green, blue, pink*, and *yellow*.

**[Figure 1]**

Four objects were presented sequentially in the center of the screen, on a white background. Their size was 3x3cm. In the control condition no feature was repeated, so that the four memory objects consisted of four different shapes, four different textures, and four different colors, schematically: Aa*A,* Bb*B*, Cc*C*, Dd*D*. In the experimental condition each feature was repeated once, so that every object in working memory shared one or two features with another object, schematically: Aa*A*, Ab*B*, Bb*C,* Cc*C.*

A fifth object was the probe for which subjects had to decide whether or not it matched one of the four memory objects. We decided to probe one memory object in each list to make the tasks easy and short. Via self-report we made sure that people were not able to verbally code memory lists. In each condition half of the probes were *positive*; they exactly matched one memory object. *Negative* probes contained two features of one memory object and a third feature that was either *new*, which means not part of any list object, or it was *swapped*, which means part of at least one of the other three memory objects. In the experimental condition *swap* probes were constructed in two different ways. Either a repeated feature was replaced by a non-repeated one (*swap1*) or the other way round, a non-repeated feature was replaced by a repeated one (*swap2*). An example for all types of probes depending on memory lists in both conditions is presented in Figure 2.

**[Figure 2]**

There is one complication. In the control condition, *swap1* probes consisted only of non-repeated features. In the experimental condition, however, *swap1* probes could contain no or one repeated feature. *Swap2* probes could contain two or three repeated features. Thus, there were 20 *swap1* probes with no repeated feature in the control condition. There were 10 *swap1* probes with no or one repeated feature, as well as 10 *swap2* probes with two or three repeated features in the experimental condition.

In summary, 80 of the 160 trials belonged to the control condition, and 80 to the experimental condition. Assignments of repeated features to objects and to feature dimensions, the position of the memory items in the list, and the list position of the probed item, were chosen at random for each trial and each subject.

**Procedure**

Participants first underwent some standard baseline tests of our laboratory. They completed a demographic questionnaire and several tests concerning their mental and visual abilities. The digit symbol test of the HAWIE-R (Tewes, 1991) measured nonverbal intelligence and the vocabulary test MWT-A (Lehrl et al. 1991) measured verbal intelligence. After instruction, participants chose the right or left arrow key to indicate positive probes; the other key was assigned to negative probes.

Each trial started with the presentation of a small cross for one second in the center of the screen. This cross disappeared and four objects appeared sequentially, each for one second, followed by a 100ms blank screen. Following the fourth memory object and a 500ms blank screen, the probe was presented. The probe remained on the screen until participants entered a response by pressing an arrow key. Immediately after the response, a smiley indicated if the answer was right or wrong; it remained on the screen for 1000ms. Thereafter, a 500ms blank screen was presented until the next trial started with the presentation of a cross for one second. Every 16 trials there was a break with feedback about the number of remaining blocks. Pressing the space bar continued the experiment.

**Data analysis**

Data analysis and graphics used R version 2.15.0. (R Development Core Team, 2012). Item-level accuracy and latency data were analyzed with linear mixed models (LMMs) including participants as a random factor. We used the *lmer* program of the *lme4* package (Bates, Maechler & Bolker, 2011). Given the large number of observations, the t-statistics for the contrasts approximate a normal distribution and t-values >2.0 are interpreted as significant. Whereas classic significance testing does not assess the strength of evidence in favor of the null hypothesis, this can be achieved through Bayes Factors (Raftery, 1995; Wagenmakers, 2007). To obtain the Bayes Factors we used repeated measures ANOVA tables (function *anova* of the standard *stats* package in R; R

Development Core Team, 2012) as described by Masson (2011). The Bayes Factor quantifies the relative strength of evidence for one hypothesis compared to the other. By multiplying the Bayes Factor with the ratio of the prior probabilities one can obtain the ratio of the posterior probabilities that one or the other hypothesis is correct given the data. For example, assuming equal prior probabilities for both hypotheses (1:1) and a Bayes Factor of 4, the ratio of the posterior probabilities would be 4:1, and therefore the data would support the null hypothesis 4 times as much as the alternative hypothesis. For graphics we used the *ggplot2* package (Wickham, 2009).

For accuracy analysis, all data points were taken into account (*N*: 34x160=5440). Because accuracy on individual trials is a binary variable, inferential statistics were based on a generalized linear mixed model using the binomial family with a logit link function, implementing a logistic regression model. For ease of interpretation, effects are reported and visualized in the familiar probability-correct scale. Reaction time (RT) analysis included only RTs of correct answers. This procedure left us with 71% of the original data. Distributions of RT data typically violate the assumption of normality. To find the best transformation for our RT data to approximate normality we used a Box-Cox transformation (function *boxcox* of package MASS in R; Venables & Ripley, 2002) as suggested in Kliegl, Masson, and Richter (2010). The Box-Cox transformation finds the appropriate power parameter lambda for transforming RTs. The optimal lambda regarding homoscedasticity and a 95% confidence interval was -0.5, which indicates a square-root transformation. Therefore RTs were raised to the power of -0.5. Afterwards they were multiplied by -1 to keep the original rank order from low to high RTs. The need for a square-root transformation of RTs was also indicated by analyses of LMM residuals. Statistical inferences, however, did not depend on the transformation; the same effects were significant for untransformed RTs.

Main analyses focus on the effect of the seven design cells obtained by combining two conditions of feature repetition (control: no repetition vs. experimental: repetition) with their three or four probe types, respectively. To test hypotheses of theoretical interest, we specified six planned comparisons: (C1) main effect of repeated features (i.e., control vs. experimental condition;

excluding *swap2* probes with more than one repeated feature because they were least comparable to the probes in the control condition), (C2) contrast between *positive* probes and *negative* probes with *new* features, (C3) contrast between *negative* probes with one *new* feature and negative *swap1* probes with one swapped feature , (C4) the interaction of C1 and C2, (C5) the interaction of C1 and C3, and finally, (C6) the contrast between the two kinds of *negative swap* probes in the experimental condition, that is *swap1*, swapping a unique feature to replace a repeated one, versus *swap2*, swapping a repeated feature to replace an unique one.

## Results

### Effects of feature repetition and probe type

*Accuracy.* Figure 3(a) displays the accuracies in control and experimental condition based on different probe types.

**[Figure 3]**

There was neither a main effect of experimental vs. control condition (C1) nor any interaction between this factor and any of the two contrasts comparing negative probes (C4 and C5); all |*z-values*| < 1.3. *Negative new* probes were recognized with higher accuracy (79%) than *positive* probes (72%; *C2 coefficient*: 0.67, *SE*=0.15, *z*=4.2). *Negative new* probes were also recognized with higher accuracy than *negative swap1* probes (64%; *C3 coefficient:* 1.47, *SE*=0.19, *z*=7.7). In addition, *negative swap1* probes in the experimental condition with up to one repeated feature were recognized more accurately than *negative swap2* probes with two or three repeated features (47%; *C6 coefficient:* 0.71, *SE*=0.16, *z*=4.5). We calculated the Bayes Factor for the main effect of condition using the classic repeated measures ANOVA table with accuracy data as dependent variable. The Bayes Factor for the main effect of feature overwriting in our accuracy data was 3.7. Therefore the accuracy data provides no evidence for a main effect of feature overwriting when assuming equal prior probabilities (Raftery, 1995).

*Latency.* RTs of the correct answers are plotted in Figure 3(b). Again, there was no evidence in support for feature overwriting: Neither the main effect of experimental vs. control condition

(C1) nor any of the interactions between this factor and either of the two negative probes (C4 and C5) were significant; all |*t-values*|<1.3. *Positive* probes were recognized faster (1141ms) than *negative new* probes (1201ms; *C2 coefficient:* -0.09, *SE*=0.01, *t*=-5.9), and these in turn were recognized faster than *negative swap1* probes with none or one repeated feature (1320ms; *C3 coefficient:* -0.06, *SE*=0.02, *t*=-3.0). There was also a non-significant trend in the expected direction for faster recognition of *negative swap1* probes with up to one repeated feature (1329ms) than *negative swap2* probes with two or three repeated features (1425ms; *C6 coefficient:* -0.03, *SE*=0.02, *t*=-1.6). We computed the Bayes Factor out of the repeated measures ANOVA with untransformed RTs of correct answers as dependent variable. The Bayes Factor for the main effect of condition was 5.2. That means our RT data provides no evidence for a main effect of feature overwriting (Raftery, 1995).

*Serial position curves.* Given the null effect of feature repetition for accuracy and latency data we checked whether the null effect of the experimental manipulation extended to the shape of serial-position curves. It is well established that initial and final stimuli are represented better in memory then those in between (Oberauer, 2008; Monsell, 1978; Ratcliff & Murdock, 1976). This enhanced performance is called *primacy effect* for stimuli right at the beginning of a list and *recency effect* for stimuli at the end of a list (Crano, 1977). If feature overwriting happens primarily in one direction, causing reduced primacy or recency effects in the experimental compared to the control condition, it might lead to no difference overall between the two conditions. Accuracies and correct RTs for all *positive* probes of control and experimental condition, depending on position of the probed list item, are displayed in Figure 4.

**[Figure 4]**

In Figure 5 the accuracies and RTs of correct answers of all *negative* probes are plotted. Obviously, there was no reduced primacy or recency effect in the experimental condition.

**[Figure 5]**

**Discussion**

### No evidence for feature overwriting

There was no evidence for feature overwriting. Accuracies and latencies were comparable for all corresponding probe types across conditions. There was no main effect of condition and no interaction between condition and probe type. The only finding favoring feature overwriting is that *negative swap1* probes in the experimental condition with up to one repeated feature were recognized more accurately than *negative swap2* probes with two or three repeated features. However, the effect is absent in our RT data and therefore not convincing. We obtained the expected primacy and recency effects of serial position curves, but again, curves were similar for experimental and control condition, there was no evidence for a modulation by differential effects of feature overwriting. The Bayesian approach suggests that our data supports the null hypothesis and provides no evidence for an effect of feature overwriting.

### Evidence for the extra-list feature effect

On the positive side, our results provide support for the extralist-feature effect discovered by Mewhort und Johns (2000): Features not matching any object currently held in working memory may be easily and rapidly detected as extra-list features, generating a tendency to reject the probe. In our experiment, this translates into faster and more accurate rejections of *new* probes – with features that are not part of a current memory list – compared to *swap* probes that mismatch all list objects but are composed entirely of features that were presented in one or another list object. The contrast between *negative new* and *negative swap* probes in our experiment (i.e., contrast C3) represents a test of this proposal. *Negative new* probes were recognized with higher accuracies and shorter latencies than *negative swap* probes. We defer further discussion of this finding until after Experiment 2.

## EXPERIMENT 2

One potential weakness of Experiment 1 is that the number of feature repetitions varied randomly across probe types. Specifically, memory objects in the experimental condition contained either one or two repeated features. Thus, positive probes in this condition had one or two repeated features. There is also variance in the number of repeated features in negative probes, due to a random construction of probes. A post-hoc analysis of the data of Experiment 1 (Jünger, 2009) suggested that this variance in number of feature repetitions may have contributed to accuracy and latency effects. As the construction of probes was random, however, there were on average as few as five observations per subject in some conditions — too few and not balanced enough for statistical analysis. To address this ambiguity, a second experiment was conducted in which memory lists remained the same as in Experiment 1. But in Experiment 2, all probes in the experimental condition were constrained to a maximum of one repeated feature. The question was if we can replicate the null-effect of repeating a feature in the experimental condition with a more tightly controlled design. Furthermore, we split the experiment into two sessions with fewer trials each than in Experiment 1, to make sure that participants remained fully alert until the end of the session.

## Method

### Participants

Thirty people were drawn from the same pool as before. None of them had participated in the first experiment; one of them was excluded because of color blindness. The age of the remaining 21 female and 8 male participants ranged between 16 and 28 with a mean of 23.8 and a standard deviation of 3.8 years. For their attendance in two experimental sessions, which took about 25 minutes each, they received 8€ or credits for participation. All participants had normal or corrected-to-normal vision.

### Stimuli

Stimuli were the same as in Experiment 1, but this time we changed the probes in the experimental condition. Whereas *positive* probes in the experimental condition of Experiment 1 had one or two repeated features, they had only one repeated feature in Experiment 2. Whereas *negative new* probes in the experimental condition of Experiment 1 had zero, one or two repeated features, they had only zero repeated features in Experiment 2. Whereas *negative swap* probes in the experimental condition of Experiment 1 had zero, one, two or three repeated features, they had only zero or one repeated feature in Experiment 2.

There were again 7 design cells: 3 probe types in the control condition (*positive, new,* and *swap*) plus 4 probe types in the experimental condition (*positive, new, swap(1:1:1)* with no repeated feature, and *swap(2:1:1)* with one repeated feature). In total there were 200 trials, 100 in the control and 100 in the experimental condition, of which 50 in each condition were *positive*. Ten of the *negative* probes were *new* and contained one feature that was not part of the memory list. The other 40 *negative* probes in each condition contained a swapped feature. Again, this time all *swap* probes in the experimental condition were constructed by replacing a repeated feature by a non-repeated one. As a consequence, these probes had either none or one repeated feature in approximately 20 trials each.

### Apparatus and Procedure

Apparatus and procedure were the same as in Experiment 1 except as noted in the previous section. The 200 experimental trials were split into two sessions of 100 trials each. Optional breaks occurred after blocks of 20 trials.

## Results

For data preparation the same procedures as in Experiment 1 were used. Accuracy analysis was carried out on all data points (*N*: 29x200=5800). 70% of the data were correct responses and could therefore be used for analyzing reaction times (RT). Again, the optimal power coefficient lambda determined by Box-Cox transformation was -0.5, and reaction times were square-root transformed.

Linear mixed-effects models with six planned comparisons were computed: (C1) main effect of condition (i.e., control vs. experimental), (C2) contrast between *positive* probes and *negative* probes with *new* features, (C3) contrast between *negative* probes with *new* features and *negative* probes with *swap* features, (C4) the interaction of C1 and C2, (C5) the interaction of C1 and C3, and finally, (C6) within the experimental condition, the contrast between *swap* probes with no repeated feature and *swap* probes with one repeated feature.

**Effects of feature repetition and probe type**

*Accuracy.* Figure 6(a) displays accuracies in control and experimental conditions based on different probe types.

**[Figure 6]**

Feature repetition had no significant effect on percentages of correct answers (C1). There was only a significant main effect of probe type. *Positive* probes were recognized less well with 71% than *negative new* probes with 80% (*C2 coefficient:* -1.03, *SE*=0.22, *z*=-4.6). *Negative new* probes were rejected with higher accuracy than *negative swap* probes with 67% of correct answers (*C3 coefficient:* 1.38, *SE*=0.23, *z*=6.1). No other contrast achieved significance. The Bayes Factor for the main effect of condition in our accuracy data was 2.2.

*Latency.* Correct RTs are plotted in Figure 6(b). Again, there was no significant main effect of repeating features (C1). Reactions to *positive* probes (1044ms) were faster than to *negative* new probes (1068ms; *C2 coefficient:* -0.04, *SE*=0.02, *t*=-2.1). *Negative new* probes were rejected faster than *negative swap* probes (1148ms; *C3 coefficient:* -0.05, *SE*=0.02, *t*=-2.4). No other contrasts became significant. The Bayes Factor for the main effect of condition in our RT data was 1.8.

**Discussion**

Experiment 2 replicated the findings of Experiment 1. Again there was no evidence for feature overwriting. There was no difference in performance and latency between experimental and control condition. Bayes Factors again indicated no evidence for an effect of feature overwriting. Following Masson (2011) we finally aggregated the evidence across our two experiments to provide further support for the null hypothesis. We merged the comparable probe types of Experiment 1 and 2 in one data frame. Taken together our data still provides no evidence for a main effect of feature overwriting, neither in accuracy data (Bayes Factor = 3.3) nor in RT data (Bayes Factor = 5.2).

For recognition probes with *new* features, the lack of a significant main effect of feature repetition (C1) on performance in Experiments 1 and 2 is a replication of the results of Mewhort and Johns (2000). They compared *new* probes (i.e., probes with one extralist feature) with regard to how many times their intralist feature occurred in the memory list. Rejection of *new* probes with a feature presented once in the memory list (and a new feature) did not differ from rejection of probes with a feature presented twice in the memory list (and a new feature). *New* probes in the experimental condition of Experiment 1 could contain zero, one or two repeated features together with a new one. Further analyses of our data showed that there was no significant decrement in performance with raising number of repeated features. That means the extralist-feature effect had a strong impact, even when more than just one feature in the probe was presented twice.

Repetition of more than one feature in a memory list in *swap* probes led to a tendency to erroneously accept the probes more often in Experiments 1 and 2. This can be seen in the decreasing accuracy for *swap* probes with increasing number of repeated features in Experiment 1 (C6, comparing *swap1* and *swap2* probes). This phenomenon can be explained by a greater number of matches of probe features with list features if there are repeated features in the probe. One possible explanation is offered by dual-process theories of recognition. Dual-process theories (Yonelinas, 2002; Oberauer, 2008) assume that recognition is based on two sources of information: *familiarity* and *recollection*. Applied to the present recognition tasks, familiarity reflects a feeling of knowing a stimulus regardless of the context in which it was presented. It is assessed automatically for each probe and reflects the degree of match between that probe and recently encountered stimuli. Recollection refers to a memory of the episode in which a stimulus was encountered. It is the retrieval of an episode with a stimulus in a specific context. The finding that *positive* probes and *swap* probes were more likely to be accepted when they contained more repeated features suggests that repeating a feature increases familiarity, thereby generating a tendency towards acceptance, regardless of whether the probe actually matches an object in the memory list (in the case of *positive* probes) or not (in the case of *swap* probes). Perhaps feature overwriting on one hand weakens recollection, resulting in a weaker tendency to accept a probe and on the other hand strengthens familiarity, resulting in an increased tendency to accept a probe. Perhaps the two processes of familiarity and recollection produce opposite effects that are cancelling each other. Possibly, at some point the familiarity signal overrides the recollection signal because there are so many matches with features of different objects of the memory list. However, there are several problems for this explanation of the null-effect of feature repetition. Feature repetition can increase familiarity only if repeated features are actually represented by additional representational strength of that feature (e.g., by the additional recruitment of feature units in a neural network). One premise of the feature-overwriting model, however, is that there is a limited pool of neurons to represent a given feature, which must be shared between the representations of several objects with that feature. If a feature-coding neuron cannot be part of two objects in working memory, then a repeated feature cannot produce a higher familiarity signal than a non-repeated one. By assumption, whether the feature is presented once or twice, the total amount of feature-coding neurons should remain the same and hence, familiarity of that feature should remain the same. Another problem for the dual-process explanation is that memory for repeated features in the verbal domain does not benefit from familiarity, although there are familiarity effects, too. Oberauer & Lange (2009) found familiarity effects for letters in three-letter nonwords. Lange & Oberauer (2005) showed that memory for three-letter nonwords suffers from feature overwriting. It is rather unlikely that the two processes familiarity and recollection cancel each other in the visual domain, but not in the verbal domain.

Another potential limitation of the recognition paradigm in testing the feature overwriting hypothesis is the possibility that probes themselves, which share features with memory objects, generate feature overwriting. Although the amount of feature overwriting by the probe is equal in both conditions and the probe had not to be memorized.

An alternative explanation for the null-effect of feature repetition is that depending on the algorithm used to calculate a matching signal, feature repetition could result in no effect. But algorithms that can predict our results do ignore overwritten features or do not assume that features are overwritten. In other words, such algorithms would explain the lack of an effect of feature overwriting by ignoring feature overwriting. For example, with a variation of Luce´s choice rule, as used in the feature-sampling theory of recognition (Brockdorff & Lamberts, 2000), we can compute the possibility to accept a probe, as:

*P(yes)* = .

Here, *B* is the number of matches with background elements. If overwritten or missing features are ignored in this algorithm, we have 100% congruency between all *positive* probes in both conditions and the probed memory items. This could explain the lack of an effect for *positive* probes. It cannot explain – however – why our *swap* probes with more repeated features were more likely to be accepted.

To rule out any explanation of our null- effect in terms of familiarity and recognition decision algorithms that might hide the effect of feature overwriting, we changed the paradigm and used cued recall instead of recognition in a third experiment.

## EXPERIMENT 3

Experiment 3 was a recall paradigm using the same memory lists as in Experiment 1 and 2. We decided to keep the list properties of the first two experiments with four memory items containing three features, to test whether results change with recall instead of recognition. Participants had to recall the remaining two features of a memory object, given one non-repeated feature of that object as cue. This design allowed us to analyze possible effects of feature overwriting within and between the three different types of features: *shape*, *texture,* and *color.*

### Method

#### Participants

We tested 26 younger adults. Most of them were students at the University of Potsdam, 20 of them were female. None of them had participated in the first two experiments and all of them reported normal or corrected-to-normal vision. The age of the participants ranged between 16 and

37 years, with a mean of 24.5 and a standard deviation of 4.9 years. For their attendance in the 40 minutes experiment, they received 7€ or credits for participation.

**Stimuli**

Memory objects were the same as in Experiment 1, with one exception. To minimize potential feature overwriting effects by cues we now used *light blue* to replace *black* in the memory objects, and used *black* only for recall cues. Further, cues contained a new *texture shaded* and a *random shape* (i.e., a jagged polygon). The cue was always a non-repeated feature of one memory object, so that it uniquely identified one memory object for recall. This feature was combined with neutral features on the other two (to-be-recalled) dimensions; for instance, when the cue used *color* to cue an object, that object's color was combined with a *shaded texture* that never occurred in a memory object and with a *random shape* that never occurred in a memory object. Cues were presented in the center of the screen with all six feature values of the first to-be-recalled feature dimension (e.g., the six shapes) arranged on a virtual circle around the cue. Cues remained on the screen until participants made their response. After that, the second to-be-recalled feature dimension (e.g., texture) was probed by displaying the six possible values of that feature dimension (i.e., the six possible textures) arranged on a new virtual circle around the same cue. Figure 7 provides an example of the cued recall. The order of probing for the two to-be-recalled feature dimensions was determined at random.

**[Figure 7]**

In total there were 144 trials, 72 in the control and 72 in the experimental condition. The session was divided into seven blocks of 24 trials each. The first 24 practice trials were not recorded. Again, all items in the control condition consisted of non-repeated features. In the experimental condition, there were two items with one repeated feature and two items with two repeated features. The cue was always a non-repeated feature that uniquely probed one memory object.

**Apparatus and Procedure**

The experiment was conducted using a *Dell DHM* computer. The paradigm was programmed in *MATLAB* based on the operating system *Windows XP*. A 19 inch monitor was used, with a resolution of 1024 x 768 pixels and a rate of 60 Hz. After serial presentation of four memory objects, exactly as in Experiments 1 and 2, a cue surrounded by six feature values appeared on the screen. Participants chose the probed feature belonging to the cued object by clicking on it with the left mouse button. This was immediately followed by a new set of six feature values for the remaining feature dimension, until participants chose one of the six options.

## Results

Overall accuracy was 48%. The task was difficult but performance was clearly above chance, which would be 17% (i.e., one out of six feature values). First we analyzed percentages of correct answers for all three features separately. For each of the three types of features we had 3744 (*N*: 26x144) data points. 2496 responses could be used for each feature; the remaining 1248 data points were trials in which the feature was used as a cue. Linear mixed-effects models with the two planned comparisons were computed: (C01) effect of condition in non-repeated features (i.e., control non-repeated vs. experimental non-repeated), (C02) effect of repeating features (i.e., control and experimental non-repeated vs. experimental repeated). Further, we analyzed all data in one model to compare effects between the three features and position effects of the probed item. We also used chi-squared tests to test differences between observed probabilities and chance (function *chisq.test* of the standard *stats* package in R; R Development Core Team, 2012). Finally, we computed Bayes Factors as suggested by Masson (2011).

### Effects of feature repetition

*Accuracy.* Figure 8 displays the accuracies in control and experimental condition separately for all three feature dimensions.

**[Figure 8]**

The presence of repeated features in a list had no significant effect on percentages of correct answers in non-repeated features (C01). This was true for all three feature dimensions. We found a significant effect of repetition on recalling a feature (C02). Recall performance on repeated shapes was better with 58% than on non-repeated ones with 45% (*$C02_{shape}$ coefficient:* 0.55, *SE*=0.09, *z*=5.9). Also, recall performance on repeated textures was better with 53% than on non-repeated ones with 41% (*$C02_{texture}$ coefficient:* 0.53, *SE*=0.09, *z*=5.7), and recall performance on repeated colors was better with 59% than on non-repeated colors with 45% (*$C02_{color}$ coefficient:* 0.58, *SE*=0.09, *z*=6.3). A comparison between the three feature types revealed lowest accuracy for textures with 45%, compared to shapes with 49% correct answers (*coefficient:* 0.13, *SE*=0.05, *z*=2.3), and colors with 49% (*coefficient:* 0.17, *SE*=0.06, *z*=2.9).

Next, we checked whether participants systematically chose features that were part of the list, especially when they were repeated. We used chi-squared tests to test the observed relative frequencies against probabilities expected by chance. For the control condition the chance of choosing a feature that was presented in the memory list is 67% (i.e., four out of the six feature values to choose from); the observed probability was significantly higher with 85% ($\chi^2(1, N=3744)=590.6$, $p<0.001$). For the experimental condition the chance of choosing a presented feature is only 50% (i.e., three out of six feature values) because one feature value is repeated in the list; the observed probability was significantly higher with 81% ($\chi^2(1, N=3744)=2525.1$, $p<0.001$). The results suggest that participants remembered and systematically chose list features, as would be expected if those list features had higher familiarity than extra-list features.

Based on this finding, the better recall performance on repeated features could be attributed to higher familiarity of repeated than of not-repeated features. However, it could also be an artifact of a higher chance to select a repeated feature correctly, because participants tended to choose one of the familiar list features. There were only three different features presented in the experimental condition, but four different features in the control condition. We found that in the experimental condition, more than half of the chosen list features were repeated features, although only 33% (i.e., one out of three) feature values in the candidate set that appeared in the list were actually repeated in the memory list. That means participants tended to choose features that were part of the list, and this tendency was stronger when the features were repeated. This was true for correct responses as well as errors in the experimental condition. People chose the wrong repeated list feature more often (38%), than the wrong non-repeated list feature (24%); the remaining 28% of errors were due to choosing a feature that was not presented in the list.

We then calculated a repeated measures ANOVA with accuracy data as dependent variable, and the three conditions (control non-repeated, experimental non-repeated, and experimental repeated) as well as the three feature types (shape, texture and color) as independent variables to obtain the Bayes Factor for the main effect of feature repetition. The Bayes Factor was $<0.001$. That means our data provides very strong evidence for a familiarity effect of repeated features on cued recall performance (Raftery, 1995). Repeated features in the experimental condition were most often recalled with 56.7% correct answers. Non-repeated features were less often recalled with 43.1% correct answers in the control and 43.5% correct answers in the experimental condition.

*Serial position curves.* To test if feature overwriting effects were reflected in position curves, we analyzed all accuracy data depending on position. Figure 9 shows position curves for all feature conditions.

**[Figure 9]**

Again, there is no evidence for feature overwriting in position curves. Repeated features were recalled with higher accuracy than non-repeated ones at all cued positions.

## Discussion

Experiment 3, using a cued recall paradigm, strengthens the conclusions from the first two experiments. Contrary to the predictions arising from the hypothesis of feature overwriting, memory performance was not impaired by repetition of features across several feature types. Observed probabilities of choosing features that were part of the memory list were above chance. We conclude that participants preferentially chose features of the memory list. Further, participants chose repeated features more often than non-repeated ones, and thereby improved their accuracy in the experimental condition. This effect is best explained by assuming that every instance of a feature that is encoded into working memory increases that feature's familiarity. To summarize, instead of forgetting repeated visual features, people systematically chose repeated features for cued recall. Further experiments should test whether this finding can be replicated using a free recall paradigm with visual material.

## GENERAL DISCUSSION

In three experiments, memory performance was not impaired by feature repetition. Table 1 provides an overview of linear mixed-effects model statistics of the effects of interest in all three experiments.

**[Table 1]**

If anything, feature repetition improved memory. This improvement seems to come about from a strong tendency to choose the repeated feature for recall, whether this was correct or not. As a consequence, when a repeated feature was probed for recall, it had a higher likelihood of being chosen correctly by guessing. The tendency to choose repeated over non-repeated features, whether this was correct or not, could have two sources. The first explanation is that people knew which features they saw in the list independent of objects, keeping two separate records of the repeated feature, and guessing samples from the set of feature records in working memory. This seems unlikely given that we cued a specific object of the list and binding features to objects is a fast and automatic process (Allen, Baddeley & Hitch, 2006). The second explanation is that repeated features strengthen each other's representations in working memory. This is the opposite of what we would expect from feature overwriting. Mutual strengthening of representations of similar or identical contents in working memory is predicted by a different form of interference, called interference by superposition (Oberauer et al., 2012). To conclude, no evidence for feature overwriting in visual working memory was found, casting doubt on a core assumption of the feature-overwriting model (Oberauer & Kliegl, 2006).

Lange and Oberauer (2005) as well as Oberauer and Lange (2008) found worse recall for words and nonwords that contained repeated features. This effect was absent in our experiments with visual material, which raises the question why results differ across experiments. One possibility is that differences in the experimental procedure explain the different effects. In most experiments investigating feature repetition effects in verbal working memory, features of a target item in the memory list were repeated in distractors, rather than in other memory items. If participants made an effort suppressing distractors during recall, this suppression could have spilled over to memory objects sharing some features with the distractors, and this might have generated the detrimental effect of feature repetition. Our experiments were similar to Experiment 2 of Oberauer and Lange (2008) where people had to remember words followed by letters. Letters had to be recalled and not suppressed. It is conceivable that letter representations were suppressed temporarily, while recalling words sharing phonemes with those letters and this might have led to impaired recall of letters in Oberauer and Lange (2008). This would have been possible because the lists always consisted of letters followed by words, such that people knew at each point during recall whether a letter or a word was requested. In contrast, in our experiments people could never suppress a subset of items while recalling another subset because all memory representations were potentially relevant at all times during recognition or recall.

Another possibility is that feature repetition effects in verbal working memory reflect disturbances of within-word order of phonemes. In the words and nonwords of Lange and Oberauer (2005), and Oberauer and Lange (2008) features (i.e., phonemes or sub-phonemic features) had to be bound in a particular order to generate the correct (non)word. In the present experiments the visual features of an object only had to be bound together, without a further constraint on their order. In all but one experiment looking for feature overwriting with verbal material (the exception being Experiment 1 of Lange & Oberauer, 2005), phoneme repetitions occurred in different within-word positions, which could have created uncertainty about the position of repeated phonemes.

A further alternative is that there are different mechanisms of interference in verbal and in visual-spatial working memory. Baddeley (1986) assumed that verbal and visual domains of working memory are separate sub-systems. Results from PET and fMRI studies show activities in different brain areas for verbal and visual material (see Baddeley, 2007, for a review). Therefore, it is conceivable that different mechanisms operate in visual and verbal working memory, although this is not necessarily the case. Saito et al. (2008) describe extensively how visual and verbal short-term memory systems could operate in a similar way, even if they involve different networks in the brain.

Finally, phonemes might be a special content of working memory that suffers from feature overwriting. In memory tasks with verbal material, people usually transform letters into phonemes. In our experiments people did not use phonemes. Our participants reported that they were not able to verbally code the memory objects during the tasks. Schweppe, Grice, and Rummer (2011) found that acoustic similarities between syllables impair written and oral recall of word fragments. Articulatory similarity impaired recall only when people recalled lists orally. Thus, feature overwriting may only occur when people memorize and recall phonemes. Saito et al. (2008) provide further evidence for this assumption. They tested Japanese native speakers using a verbal recall task with kanji characters varying systematically in visual and phonological similarity. When using articulatory suppression, there was neither an effect of visual nor of phonological similarity on recall performance independent of order. Only order errors occurred more often in visually similar material under articulatory suppression. This finding can be explained by similarity-based confusion but not feature overwriting.

To summarize, feature repetition in verbal experiments could have led to temporary feature suppression, or to order errors within words, rather than to feature overwriting. Alternatively, feature overwriting may affect exclusively phoneme representations. In the experiments reported here people were not able to verbally code the visual memory objects. Feature repetition neither impaired recognition nor cued recall performances. Therefore, it seems reasonable to conclude that in visual working memory there is no evidence for feature overwriting, as conceptualized as one capacity limiting mechanism in the interference model of Oberauer and Kliegl (2006).

**REFERENCES**


Allen, R. J., Baddeley, A. D., & Hitch, G. J. (2006). Is the binding of visual features in working memory resource-demanding? *Journal of Experimental Psychology: General, 135*, 298-313.

Baddeley, A. D. (1986). *Working memory*. Oxford: Clarendon Press.

Baddeley, A. D. (2007). *Working memory, thought, and action*. New York: Oxford University Press.

Bates, D., Maechler, M., & Bolker, B. (2011). Linear mixed-effects models using S4 classes. [Software] R Paket Version 0.999357-35. URL http://www.R-project.org.

Brockdorff, N., & Lamberts, K. (2000). A feature-sampling account of the time course of old–new recognition judgments. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 26*(1), 77.

Crano, W. D. (1977). Primacy versus recency in retention of information and opinion change. *Journal of Social Psychology, 101*, 87-96.

Fallon, A. B., Groves, K., & Tehan, G. (1999). Phonological similarity and trace degradation in the serial recall task: When CAT helps RAT, but not MAN. *International Journal of Psychology (Special Issue: Short-Term/Working Memory)*, *34*, 301-307.

Fell, J., & Axmacher, N. (2011). The role of phase synchronization in memory processes. *Nature Reviews Neuroscience*, *12*(2), 105–118.

Feldman, J. (2013). The neural binding problem(s). *Cognitive Neurodynamics*, *7*(1), 1–11.

Jünger, E. (2009). *Merkmalsüberschreibung im visuellen Arbeitsgedächtnis* [Feature overwriting in visual working memory]. Diploma thesis. Potsdam: University of Potsdam.

Kliegl, R., Masson, M.E.J., & Richter, E.M. (2010). A linear mixed model analysis of masked repetition priming. *Visual Cognition*, *18*, 655-681.

Lange, E. B., & Oberauer, K. (2005). Overwriting of phonemic features in serial recall. *Memory*, *13*, 333-339.

Lehrl, S., Merz, J., Burkhard, G., & Fischer, B. (1991). *Mehrfachwahl-Wortschatz-Intelligenztest MWT-A* (Parallelform zum *MWT-B)*. Erlangen: Perimed-Fachbuch-Verlagsgesellschaft.

Masson, M. E. J. (2011). A tutorial on a practical Bayesian alternative to null-hypothesis significance testing. *Behavior research methods*, *43*(3), 679–690.

Mewhort, D. J. K., & Johns, E. E. (2000). The extralist-feature effect: A test of item matching in short-term recognition memory. *Journal of Experimental Psychology: General*, *118*, 346-373.

Monsell S. (1978). Recency, immediate recognition, and reaction time. *Cognitive Psychology*, *10*, 465-501.

Nairne, J. S. (1990). A feature model of immediate memory. *Memory & Cognition, 18*, 251-269.

Nairne, J. S. (2002). Remembering over the short-term: The case against the standard model. *Annual Review of Psychology, 53*, 53-81.

Nairne, J. S., Neath, I., & Serra, M. (1997). Proactive interference plays a role in the word length effect. *Psychonomic Bulletin & Review, 4*, 541-545.

Oberauer, K. (2008). How to say no: Single- and dual-process theories of short-term recognition tested on negative probes. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34*, 439-459.

Oberauer, K., Farrell, S., Jarrold, C., Pasiecznik, K., & Greaves, M. (2012). Interference between maintenance and processing in working memory: The effect of item–distractor similarity in complex span. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*, 665-685.

Oberauer, K., & Kliegl, R. (2001). Beyond resources - Formal models of complexity effects in age differences in working memory. *European Journal of Cognitive Psychology, 13,* 187-215.

Obenauer, K., & Kliegl, R. (2006). A formal model of capacity limits in working memory. *Journal of Memory and Language, 55,* 601-626.

Oberauer, K., & Lange, E. B. (2008). Interference in verbal working memory: Distinguishing similarity-based confusion, feature overwriting, and feature migration. *Journal of Memory and Language*, *58*, 730-745.

Oberauer, K., & Lange, E.B. (2009). Activation and binding in verbal working memory: A dual-process model for the recognition of nonwords. *Cognitive Psychology*, *58*, 102-136.

Oberauer, K., & Lewandowsky, S. (2008). Forgetting in immediate serial recall: Decay, temporal distinctiveness, or interference? *Psychological Review, 115*, 544-576.

Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological Methodology*, *25*, 111–164.

Ratcliff, R., & Murdock, B. (1976). Retrieval processes in recognition memory. *Psychological Review, 83*, 190-214.

R Development Core Team (2012). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

Saito, S., Logie, R. H., Morita, A., & Law, A. (2008). Visual and phonological similarity effects in verbal immediate serial recall: A test with kanji materials. *Journal of Memory and Language*, *59*(1), 1–17.

Schweppe, J., Grice, M., & Rummer, R. (2011). What models of verbal working memory can learn from phonological theory: Decomposing the phonological similarity effect. *Journal of Memory and Language, 64*, 256-269.

Tewes, U. (Ed.). (1991). *Hamburg-Wechsler-Intelligenztest für Erwachsene-Revision 1991 (HAWIE-R)*. Bern: Huber.

Venables, W. N., & Ripley, B. D. (2002). Modern applied statistics with S. [Software] R Paket Version 7.2- 47. New York: Springer. URL http://www.R-project.org.

Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems of p values. *Psychonomic Bulletin & Review*, *14*, 779-804.

Wickelgren, W. A. (1965). Acoustic similarity and retroactive interference in short-term memory. *Journal of Verbal Learning and Verbal Behavior*, *4*, 53-61.

Wickham, H. (2009). ggplot2: Elegant Graphics for Data Analysis. [Software] R Paket Version 0.8.9. New York: Springer. URL http://www.R-project.org.

Yonelinas, A. P. (2002). The nature of recollection and familiarity: A review of 30 years of research. *Journal of Memory and Language*, *46*, 441-517.

Table 1.

*Linear Mixed Effects Model Statistics of Effects of Interest in Experiment 1, 2, and 3*

| Experiment 1 | | | | | | |
|---|---|---|---|---|---|---|
| | Accuracy | Latency | | | | |
| Contrasts | Coefficient | SE | z | Coefficient | SE | t |
| C1 | -0.08 | 0.07 | -1.19 | 0.01 | 0.01 | 0.88 |
| C4 | -0.16 | 0.16 | -1.03 | -0.00 | 0.01 | -0.03 |
| C5 | 0.09 | 0.19 | 0.47 | 0.02 | 0.02 | 1.24 |
| Experiment 2 | | | | | | |
| | Accuracy | Latency | | | | |
| Contrasts | Coefficient | SE | z | Coefficient | SE | t |
| C1 | -0.05 | 0.08 | -0.68 | 0.00 | 0.01 | 0.56 |
| C4 | 0.16 | 0.22 | 0.74 | -0.02 | 0.02 | -0.93 |
| C5 | -0.16 | 0.23 | -0.72 | 0.03 | 0.02 | 1.28 |
| Experiment 3 | | | | | | |

| | Accuracy | | |
|---|---|---|---|
| Contrasts | Coefficient | SE | z |
| C01 | 0.03 | 0.07 | 0.38 |
| C02 | 0.55 | 0.05 | 10.4*** |

Note. ***$p < 0.001$, C1: control vs. experimental condition, C2 *positive* probes vs. *new* probes, C3: *new* probes vs. *swap* probes, C4: interaction of C1 and C2, C5: interaction of C1 and C3, C01: control non-repeated vs. experimental non-repeated (all feature dimensions), C02: control & experimental non-repeated vs. experimental repeated (all feature dimensions)

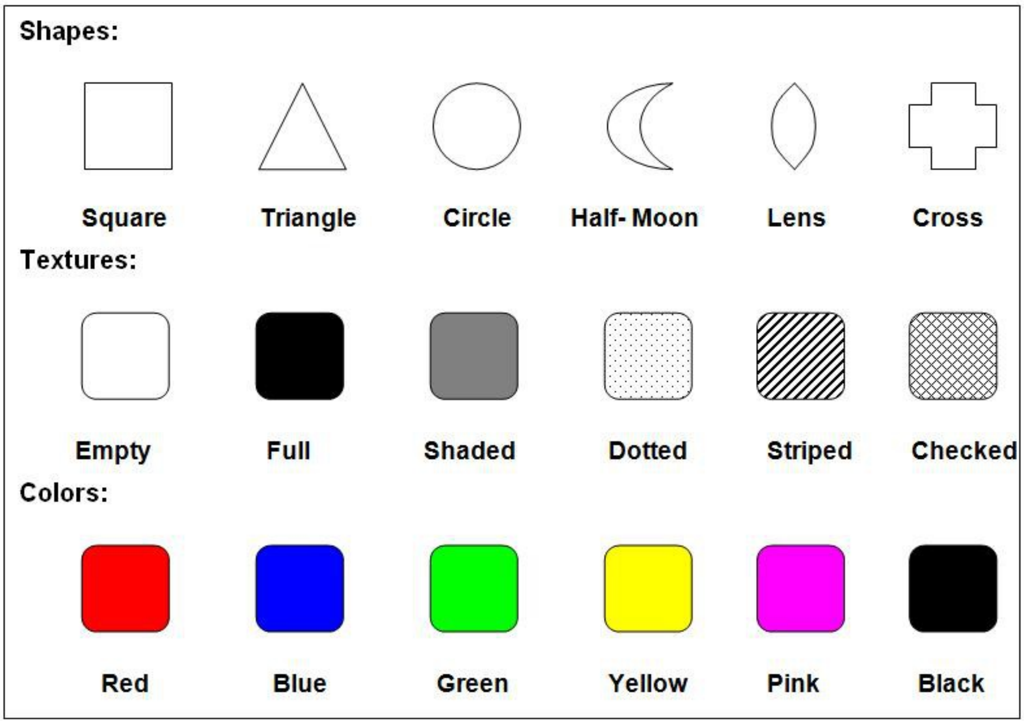


*Figure 1*. Shapes, textures, and colors.

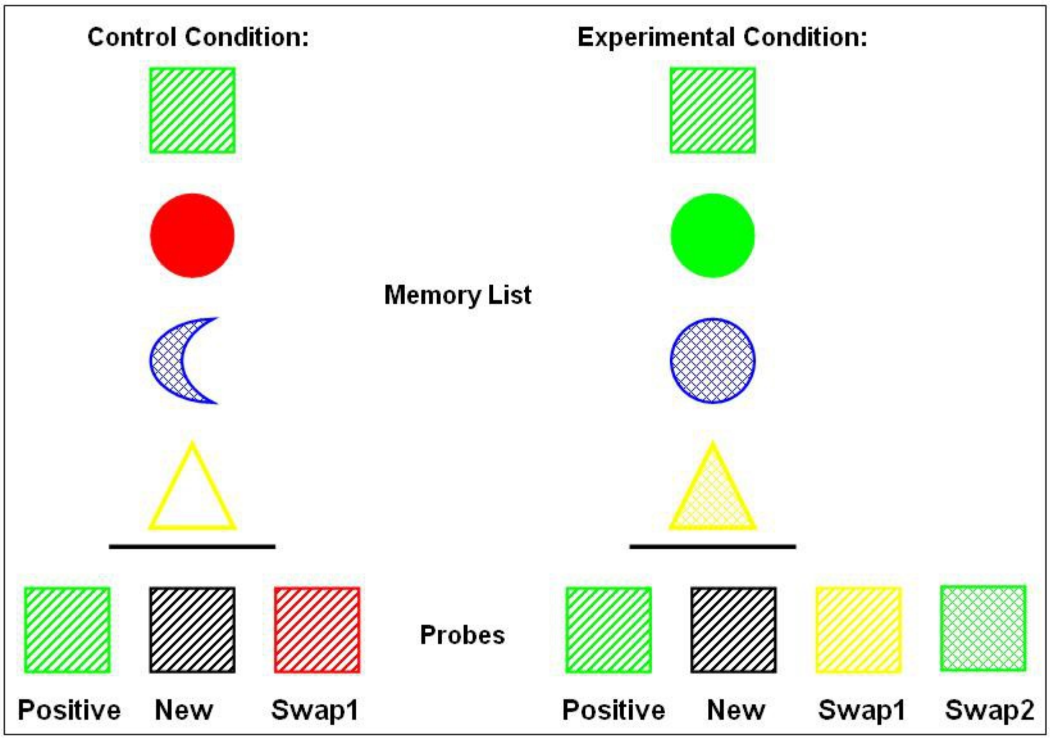


*Figure 2.* Memory lists and probe types in control and experimental condition. The number of trials in the seven conditions was 40, 20, 20, 40, 20, 10, 10 (from left to right) for a total of 160 trials per subject. The reference item of all probes is the first object, a *green square* with *stripes (*Aa*A)*. The control condition has no repeated features. The experimental has a repeated color (*green, A*), a repeated texture (*checked,* c), and a repeated shape (*circle,* B). Positive probes match one memory object completely (*green square* with *stripes*). In *new* probes, one feature of a memory object (*green*) is replaced with a feature not present in the current list (*black, X*). In control *swap1* probes, one feature (*green*) is replaced with a feature that occurred in another memory object (*red, B*). In experimental *swap1* probes, one repeated feature (*green*) is replaced with a non-repeated feature of another memory object (*yellow, C*). In experimental *swap2* probes, a non-repeated feature (*stripes*) is replaced with a repeated feature that occurred within two other memory objects (*checked,* c). By

definition *swap1* probes with one repeated feature and *swap2* probes with two or three repeated features occur only in the experimental condition.

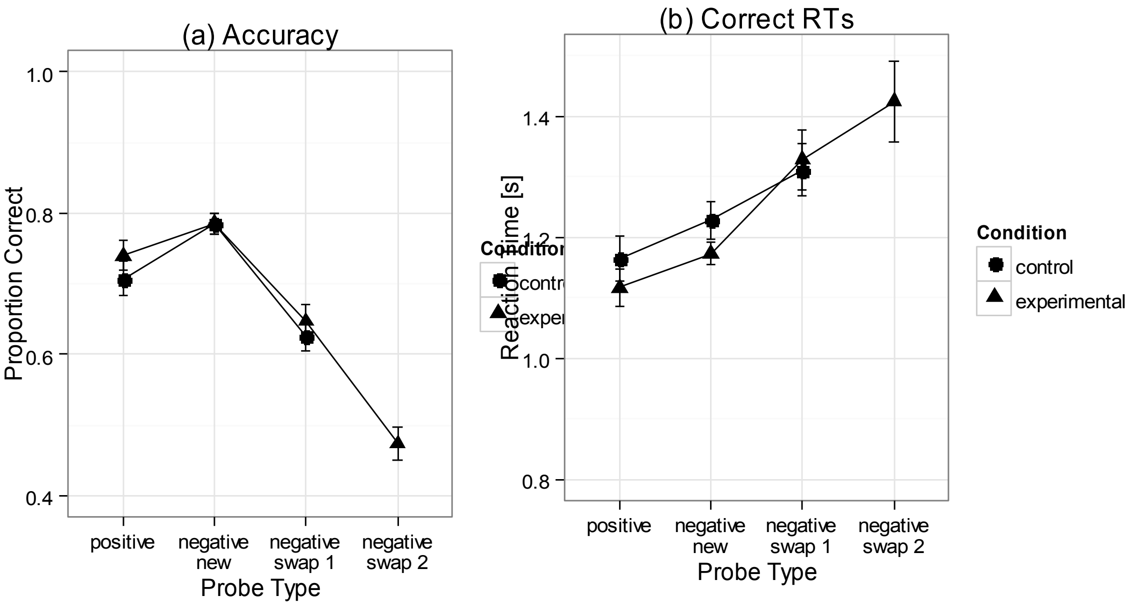


*Figure 3.* (a) Accuracies and (b) reaction times of correct answers (Correct RTs) for probe types in control and experimental condition observed in Experiment 1. Error bars are +/- 1 standard error (SE) after removal of between-subject variance.

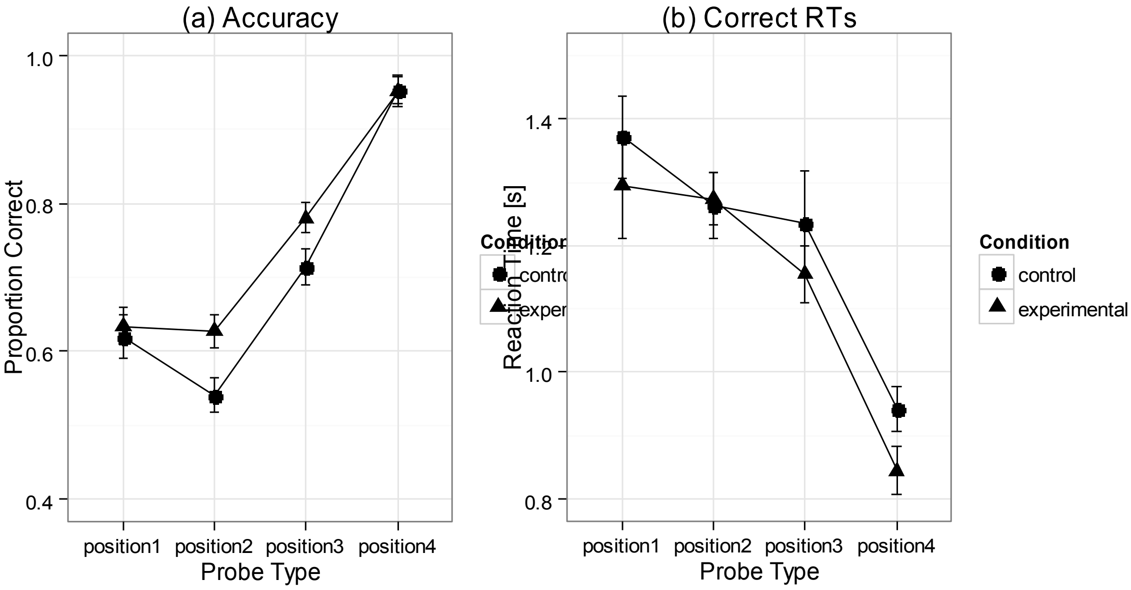


*Figure 4.* (a) Accuracies and (b) reaction times of correct answers (Correct RTs) for *positive* probes depending on the position of the probed item in the memory list observed in Experiment 1. Error bars are +/- 1 standard error (SE) after removal of between-subject variance.

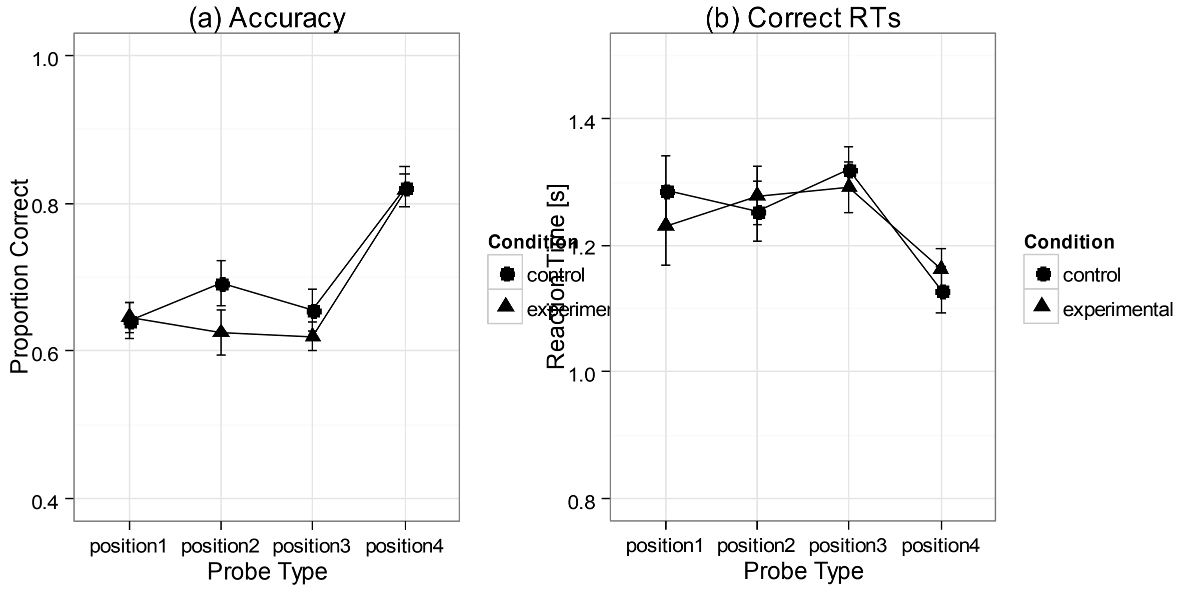


*Figure 5.* (a) Accuracies and (b) reaction times of correct answers (Correct RTs) for *negative* probes depending on the position of the probed item in the memory list observed in Experiment 1. Error bars are +/- 1 standard error (SE) after removal of between-subject variance.

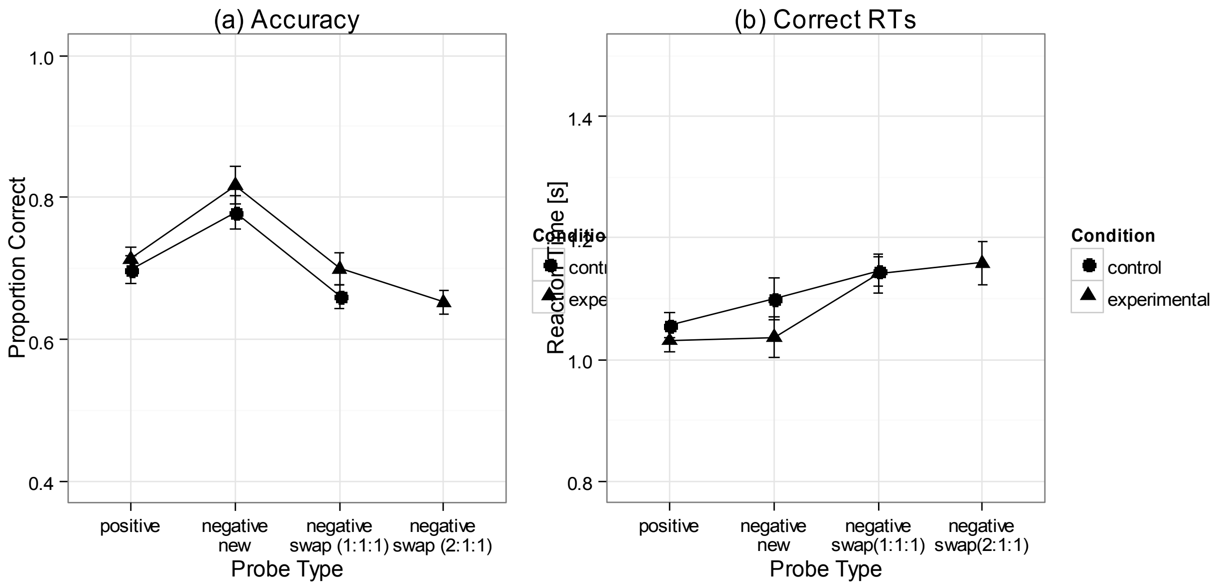


*Figure 6.* (a) Accuracies and (b) reaction times of correct answers (Correct RTs) for probe types in control and experimental condition observed in Experiment 2. Error bars represent +/- 1 standard error (SE) after removal of between-subject variance. *Negative swap* probes (1:1:1) do not contain a repeated feature, *swap* probes (2:1:1) contain one repeated feature.

*Figure 7.* Example of a cued recall trial in Experiment 3. The cue presented in the center of the screen is a *striped* texture. The participant has to remember the shape of the one striped object in the memory list. All six values of shape are arranged circular around the cue. Participants mark their choice by mouse click.

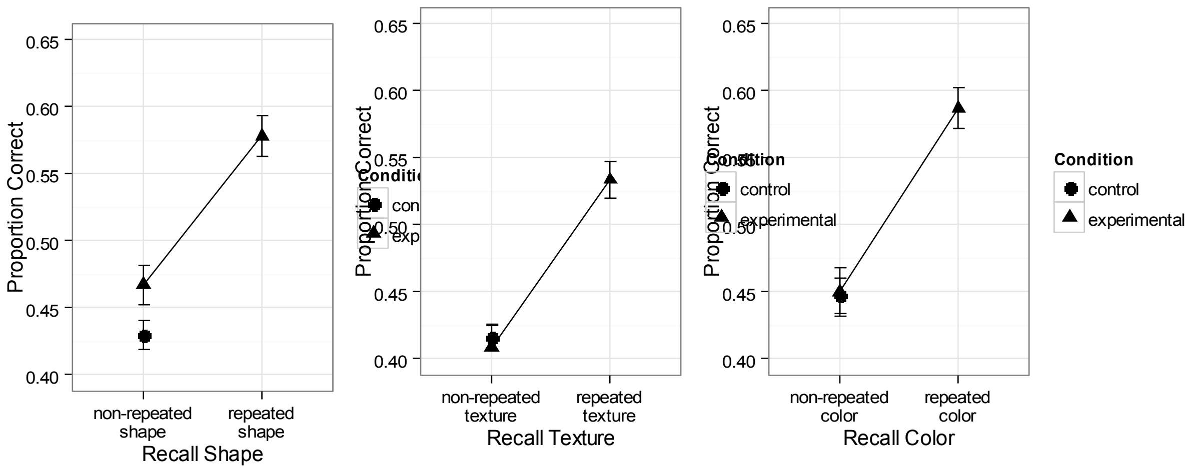


*Figure 8.* Accuracies for all feature and repetition types of control and experimental condition observed in Experiment 3. Error bars represent +/- 1 standard error (SE) after removal of between-subject variance.

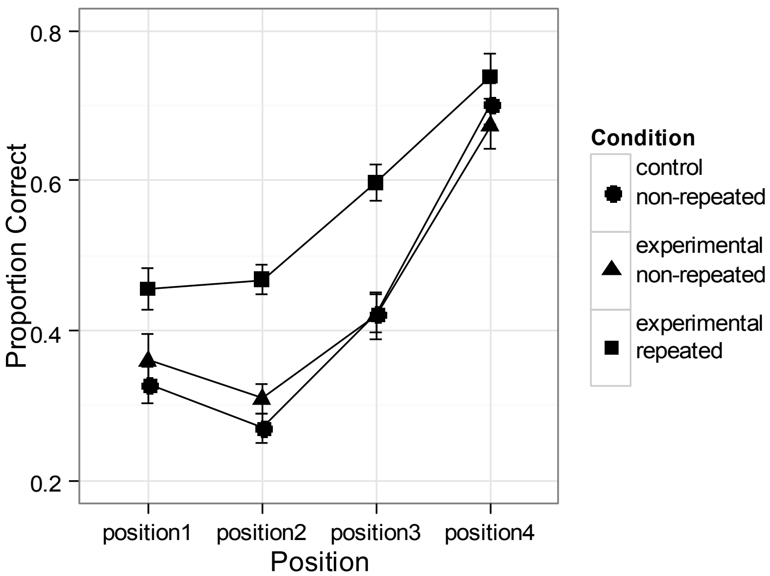


*Figure 9.* Accuracies for all feature conditions depending on the position of the probed item in the memory list observed in Experiment 3. Error bars are +/- 1 SE after removal of between-subject variance.