NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

Yuri A. Markov, Natalia A. Tiurina,
Igor S. Utochkin

DIFFERENT FEATURES ARE STORED INDEPENDENTLY IN VISUAL WORKING MEMORY BUT MEDIATED BY OBJECT-BASED REPRESENTATIONS

BASIC RESEARCH PROGRAM

WORKING PAPERS

SERIES: PSYCHOLOGY
WP BRP 101/PSY/2018

This Working Paper is an output of a research project implemented at the National Research University Higher School of Economics (HSE). Any opinions or claims contained in this Working Paper do not necessarily reflect the views of HSE

Yuri A. Markov[1], *Natalia A. Tiurina*[2],

Igor S. Utochkin[3]

DIFFERENT FEATURES ARE STORED INDEPENDENTLY IN VISUAL WORKING MEMORY BUT MEDIATED BY OBJECT-BASED REPRESENTATIONS

The question whether visual working memory (VWM) stores individual features or bound objects as basic units is actively debated. Evidence exists for both feature-based and object-based storages, as well as hierarchically organized representations maintaining both types of information at different levels. One argument for feature-based storage is that features belonging to different dimensions (e.g., color and orientations) can be stored without interference suggesting independent capacities for every dimension. Here, whether the lack of cross-dimensional interference reflects genuinely independent feature storages or mediated by common objects. In three experiments, participants remembered and recalled the colors and orientations of sets of objects. We independently manipulated set sizes within each feature dimension (making colors and orientations either identical or differing across objects). Critically, we assigned to-be-remembered colors and orientations either to same spatially integrated or to different spatially separated objects. We found that the precision and recall probability within each dimension was not affected be set size manipulations in a different dimension when the features belonged to integrated objects. However, manipulations with color set sizes did affect orientation memory when the features were separated. We conclude therefore that different feature dimensions can be encoded and stored independently but the advantage of the independent storages are mediated at the object-based level. This conclusion is consistent with the idea of hierarchically organized VWM.

JEL Classification: Z.

Keywords: visual working memory, features, objects, hierarchical encoding.

---

[1] “Laboratory for cognitive research”, National Research University Higher School of Economics, Russian Federation. E-mail: yuamarkov@gmail.com

[2] “Laboratory for cognitive research”, National Research University Higher School of Economics, Russian Federation. E-mail: natalyatyurina@gmail.com

[3] “Laboratory for cognitive research”, National Research University Higher School of Economics, Russian Federation. E-mail: isutochkin@inbox.ru

Introduction

At every moment of our perception, we interact with different objects, each having a number of various features, such as color, shape, size, etc. A limited portion of the information about these objects and their features can be used for current tasks and maintained for a short period of time in working memory (Baddeley, 1986; Baddeley & Hitch, 1974). It is consistently established that the capacity of working memory has serious limitations (e.g., Cowan, 2001; Miller, 1956). These fundamental limits are also true for the visual subsystem of working memory (VWM) which maintain and operates visual information (Alvarez & Cavanagh, 2004; Luck & Vogel, 1997). However, for a correct capacity estimate it is important to determine what is represented in VWM as a basic unit of storage. There is a long-lasting debate around this question in the VWM literature: Does VWM store whole objects or separate features?

Existing studies provide evidence that both objects (Kahneman, Treisman, & Gibbs, 1992; Lee & Chun, 2001; Luck & Vogel, 1997; Luria & Vogel, 2011; Treisman, 1999; Vogel, Woodman, & Luck, 2001; Xu, 2002; Xu & Chun, 2006; Cowan, Chen & Rouder, 2004) and features (see Brady, Konkle, & Alvarez, 2011, for review; Wang, Theeuwes, Olivers, & Wang, 2016; Wheeler & Treisman, 2002; Shin & Ma, 2017; Fougnie & Alvarez, 2011) can be units of VWM. In their seminal study, Luck and Vogel (1997) demonstrated a strong advantage of maintaining any number of features in a limited number of spatially bound objects (at least up to four features per object). The prevailing limiting factor for capacity in found by Luck and Vogel (1997) was the number of objects (~3-4) rather than the number of features. They concluded that objects are units of VWM, showing no limitation in VWM by number of features. However, other studies failed to support this strong version of object-based storage suggesting that features also can limit VWM (see Brady, Konkle, & Alvarez, 2011, for review). Two major sets evidence are used against this purely object-based account. The first set of evidence is based on findings that increasing the number of features to be remembered within an object do cause interference. For example, the increased number of features belonging to a same dimension per object significantly decreases VWM capacity for these objects (Wheeler & Treisman, 2002; Olson & Jiang, 2002; Xu, 2002). The same was found for increasing object complexity (Alvarez and Cavanagh, 2004; Hardman & Cowan, 2015; Oberauer & Eichenberger, 2013). Other studies have found that remembering two features of the same objects impaired the precision of each remembered feature, while the capacity is seemingly intact (Fougnie, Asplund, & Marois, 2010; Fougnie & Marois, 2009). The second strong line of evidence against the purely object-based account of VWM is a number of demonstrations of relative independence between features of the same object leading to their selective forgetting or swaps between remembered features of different objects (Bays, Catalao, & Husain, 2009; Bays, Wu, & Husain, 2011; Fougnie & Alvarez, 2011; Fougnie, Cormiea, & Alvarez, 2013; Pertzov, Dong, Peich, & Husain, 2012). Whatsoever, even in the presence of these feature-based limitations, VWM still consistently benefits from object-based representations: It is easier to remember several features of one object than the same number of features distributed across several objects (Fougnie et al., 2010; Fougnie et al., 2013; Wheeler & Treisman, 2002). To account for this, theorists suggested that not objects or features alone can be the units of VWM. Rather, the units are hierarchically structured “feature bundles” containing both integrated object and feature representations hierarchically linked (see Brady et al., 2011, for review; Fougnie et al., 2010). Similar ideas that VWM can be constrained by both objects and features in different ways have been proposed by other authors (Olson & Jiang, 2002; Shin & Ma, 2017; Xu & Chun, 2006).

The complicated pattern of evidence for feature-based vs. object-based storage in VWM is additionally complicated by an unclarity regarding the structure of feature memories. Specifically, it was noted that VWM performance can depend on whether remembered and tested features belong to same or different dimensions. Most experiments on features were the same dimension (Wheeler & Treisman, 2002; Olson & Jiang, 2002; Xu, 2002) which typically constitute different parts of an object (Alvarez & Cavanagh, 2004) show a significant decrement in performance with an increasing number of features per object (but see Luck & Vogel, 1997; Vogel, Woodman & Luck, 2001 for an opposite conclusion). There is no such interference between features from the same dimension (e.g., Wheeler & Treisman, 2002). This leaves room for a theory that feature-based VWM is in fact a multistorage system having separate capacities for features from different dimensions. This theory was directly tested and supported in recent studies where researchers independently manipulated the memorized set size for features from two separable dimensions, color and orientation (Wang, Cao, Theeuwes, Olivers, & Wang, 2017). They found that VWM capacity for a given feature depended on the set size in the corresponding dimension rather than joint set size in both dimensions. For example, if observers are shown six isosceles triangles, each triangle having one of two possible colors (color set size is two) and one of two possible orientations (orientation set size is also two), their ability to spot a change in either of the dimensions is rather high. If color size becomes six (each triangle has a unique color) and orientation set size remains two, it selectively impairs change detection for color but not for orientation (and vice versa if color set size stays small and orientation set size increases). These separate storages can provide an advantage when the selective encoding of one dimension and ignoring another can be required (Shin & Ma, 2017; Woodman & Vogel, 2008).

However, it is important to note that independent set size manipulations in the experiments by Wang et al. (2017) concerned features but not objects these features belonged to.

In all experiments, colors and orientations were tested in a same set of objects. If object representations facilitate feature storage in general, can they mediate the advantage of the independent feature capacities? Alternatively, these independent capacities can be purely feature-based in which case they should manifest in both unitary and separate objects.

To address this question, we have run three experiments testing VWM for color and orientation. The general approach was similar to that used by Wang et al. (2017): We orthogonally manipulated the set size within each dimension by assigning either a single or three different values and measured VWM for both dimensions. Critically, colors and orientations could be assigned to same objects (Experiment 1), different parts of spatially integrated objects (Experiment 3), or spatially separated objects (Experiment 2). Unlike Wang et al. (2017), we used a continuous report task (Wilken & Ma, 2004; Zhang & Luck, 2008) instead of a change detection task. It is justified by a fact that the former paradigm allows parametric estimation of both capacity and fidelity of VWM (Zhang & Luck, 2008), that are both known to be sensitive to feature-based and object-based load (Fougnie et al., 2010).

Experiment 1

In Experiment 1, we tested VWM for colors and orientations in a same set of three objects. In different conditions of the experiment, we assigned either three different values or a single value to each object in each dimension orthogonally. This manipulation affected both within-dimension and joint set sizes in a manner similar to that in the experiments by Wang et al. (2017). Hence, the main goal of this experiment is to test whether the principal finding of independent storages for color and orientation is replicated in our paradigm.

Methods

Participants

Twenty students from the Higher School of Economics (17 female) participated for extra course credits. The participants ranged in age from 18 to 25 years (average age was 19.93 years) and reported having normal or corrected to normal visual acuity, no color blindness and neurological problems. Before the beginning of the experiment, they signed an informed consent form. In this and subsequent experiments, sample sizes were determined based on similar studies addressing the issue of feature storage and binding in VWM and using a continuous report task (from 10 to 16; for example, Fougnie & Alvarez 2011; Fougnie et al., 2010; Bays, Catalao, & Husain, 2009; Pertzov, Dong, Peich, & Husain, 2012). The planned sample size also included a few extra participants considering a possibility of technical problems or poor performance in some participants.

Apparatus and stimuli

Stimulation was developed and presented through PsychoPy (Pierce, 2007) for Linux Ubuntu. Stimuli were presented on a standard VGA monitor with a refresh frequency of 75 Hz and 1024×768-pixel spatial resolution. Stimuli were presented on a homogeneous gray field. Participants sat approximately at 47 cm from the monitor. From that distance, screen subtended approximately 42.44 × 32.5 degrees of visual angle.

Sample displays consisted of one or three colored isosceles triangles presented in randomized positions along an imagery circumference 4.35º away from a monitor center (Figure 1). Each triangle had sides of .6º, 1.2º, and 1.2º in length. To set the positions of the three triangles on the imaginary circumference, we first generated a random rotational angle from 1º to 360º for a first triangle and then positioned the rest two triangles 120º and -120º away from the first with a ±30º-jitter. For color assignment, we used the hue wheel in the 360º HSV (hue-saturation-value) space, and for orientation assignment, we used the 360º orientational circumference. As color and orientation had the same dimensionality as spatial positions, we applied the rotational algorithm described above to set three colors and three orientations. When an experimental condition required a single color, a single orientation, or a single item to be presented, the color, orientation, or position was chosen randomly.

For memory test, outline circles were presented at the locations of sample triangles, with one thick outline indicating the location of a probed item. In trials where color was probed, the test display was surrounded by an HSV color wheel 4.35º in radius (Figure 1). In trials where orientation was probed, the test display was surrounded by a black orientational wheel with white ticks marking 30º steps (Figure 1). The probed outline turned into a solid colored circle (if color was probed) or a white oriented triangle (if orientation was probed) upon mouse click on a wheel (Figure 1).

Procedure

Each experimental trial stared with a 500-ms presentation of a sample display. Participants were instructed to memorize both color and orientation of the triangles. The sample was followed by a 1-second delay (retention interval) that, in turn, was followed by a probe screen (Figure 1). Clicking on a color or orientation wheel, participants had to adjust a corresponding attribute of the probe item to match the sample attribute presented at that location. At the beginning of the experiment, participants completed a training session. The total duration of the experiment varied between 45 and 60 minutes.

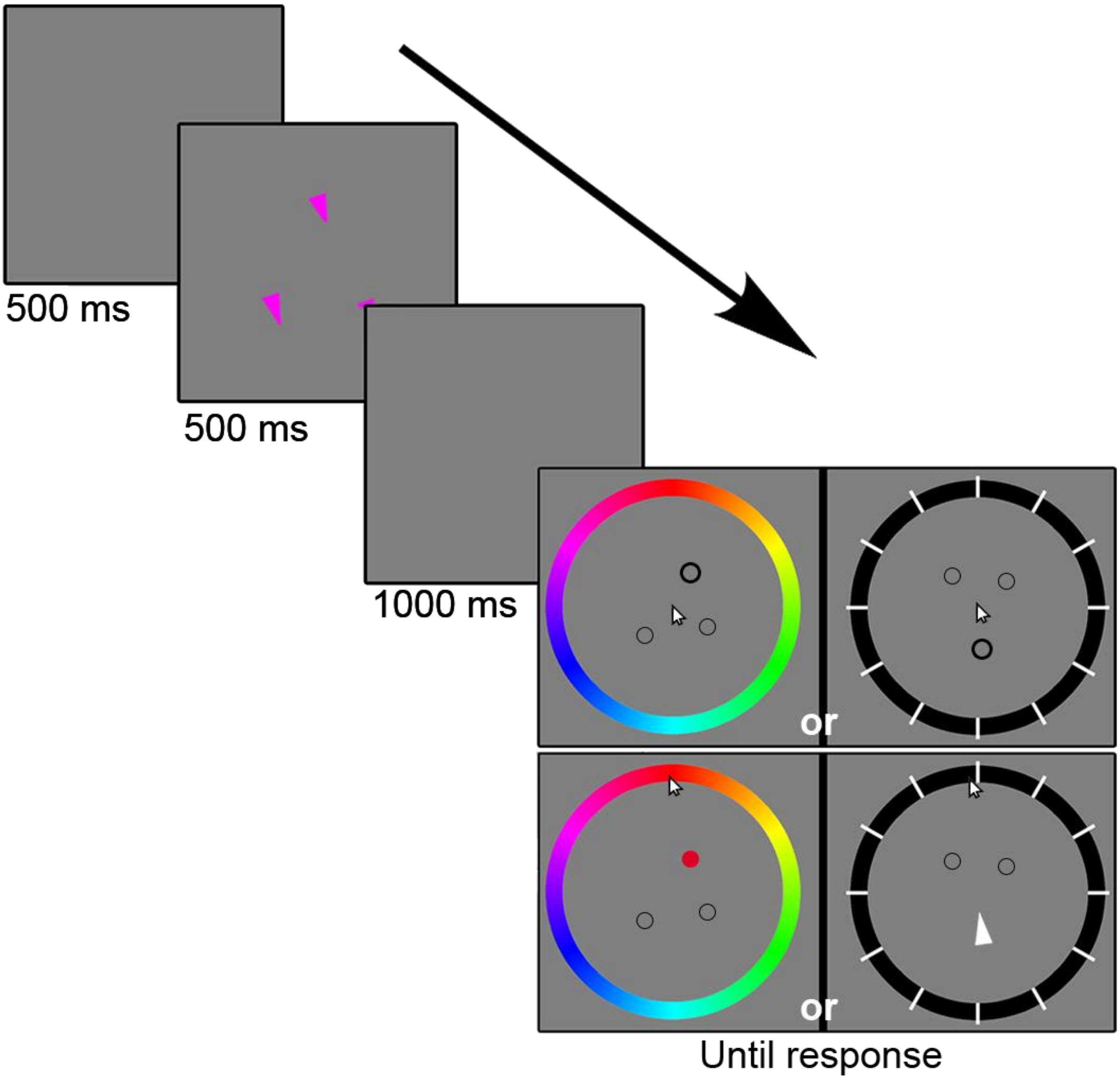

Figure 1. The time course of a typical trial in Experiment 1.

Design and data analysis

Five conditions of the Sample type were tested in Experiment 1 (Figure 2A). In four of these conditions, we orthogonally varied color and orientation set sizes in three triangles: (1) all different features (three colors and three orientations), (2) color identical (one color and three orientations), (3) orientation identical (three colors and one orientation), (4) all identical features (one color and one orientation). Condition (5) contained a single object and was used as a baseline. This baseline, in comparison with the "all identical" condition, aimed to test whether three identical feature values of three objects are indeed encoded like a single feature. In a within-subject experiment, each participant was exposed to 5 (Sample type) × 2 (Probed dimension: Color vs. Orientation) × 47 repetitions = 470 trials.

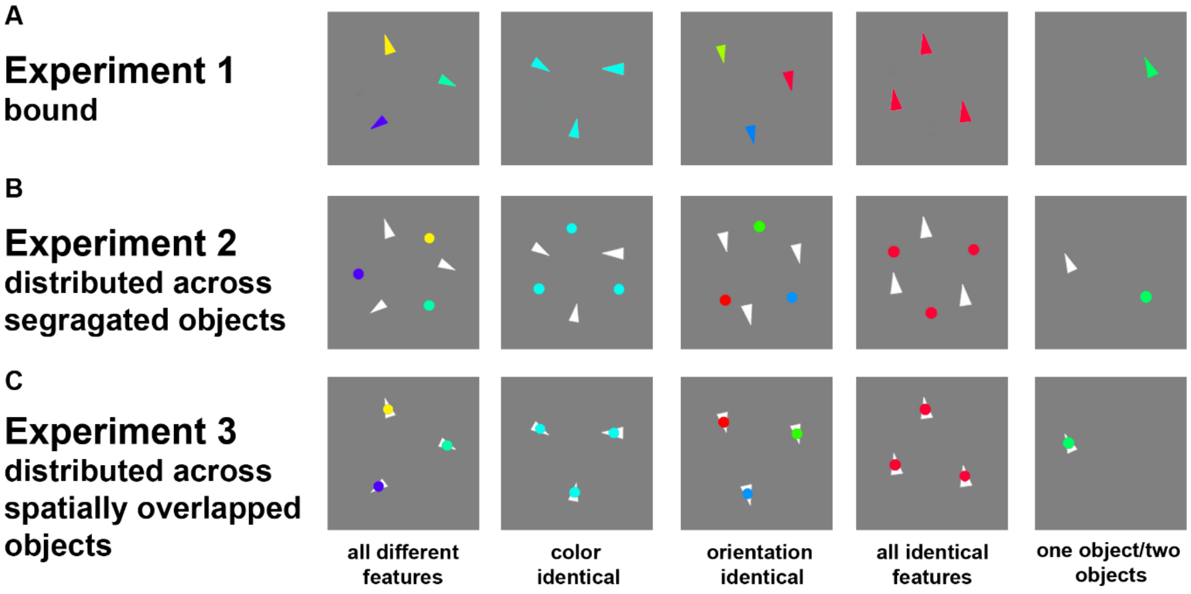

Figure 2. Example of stimuli for three experiments for five conditions (objects with all different features, objects with different color and identical orientation, objects with different orientation and identical color, objects with all identical features, one pair of features). (a) Experiment 1 with bound features in object. (b) Experiment 2 with features distributed across segregated objects. (c) Experiment 3 with features distributed across spatially overlapped objects.

For each trial, the error was calculated as an angular difference between the correct feature value and that adjusted by a participant. The distribution of errors was then analyzed using the mixture model (Zhang & Luck, 2008) implemented in MemToolbox for Matlab (Suchow, Brady, Fougnie, & Alvarez, 2013). The standard mixture model has two different parameters obtained from fitting two components of the error distribution. The first parameter is the standard deviation (*SD*) of the von Mises distributional component, that is supposed to reflect the precision of a noisy representation that is present in memory. The second parameter is the probability of random guess (P_{guess}) can be estimated as an area below the uniform component of the mixed distribution; this component is supposed to reflect randomly chosen answers when a probed item is likely to be absent in the memory (not encoded or forgotten). Reverse P_{guess} is used as an estimate for a probability that a probed element is held in VWM: $P_{memory} = 1 – P_{guess}$.

To evaluate the effect of Sample type, we applied the standard frequentist and Bayesian one-way repeated measures ANOVA to the *SD* and P_{memory} for color and orientation. The Bayes factor (BF_{10}) was calculated using JASP 0.9.0.0 (JASP Team, 2018; Wagenmakers et al., 2017) and interpreted using the standard Jeffrey's scale (1961). The Bayesian approach estimates odds of H_1 to H_0 (Rouder, Speckman, Sun, Morey, & Iverson, 2009).

Results and discussion

One participant was excluded from the analysis because she showed nearly 100% guess rate in all conditions. The results of the Experiment 1 for P_{memory} and *SD* are summarized on the Figure 3.

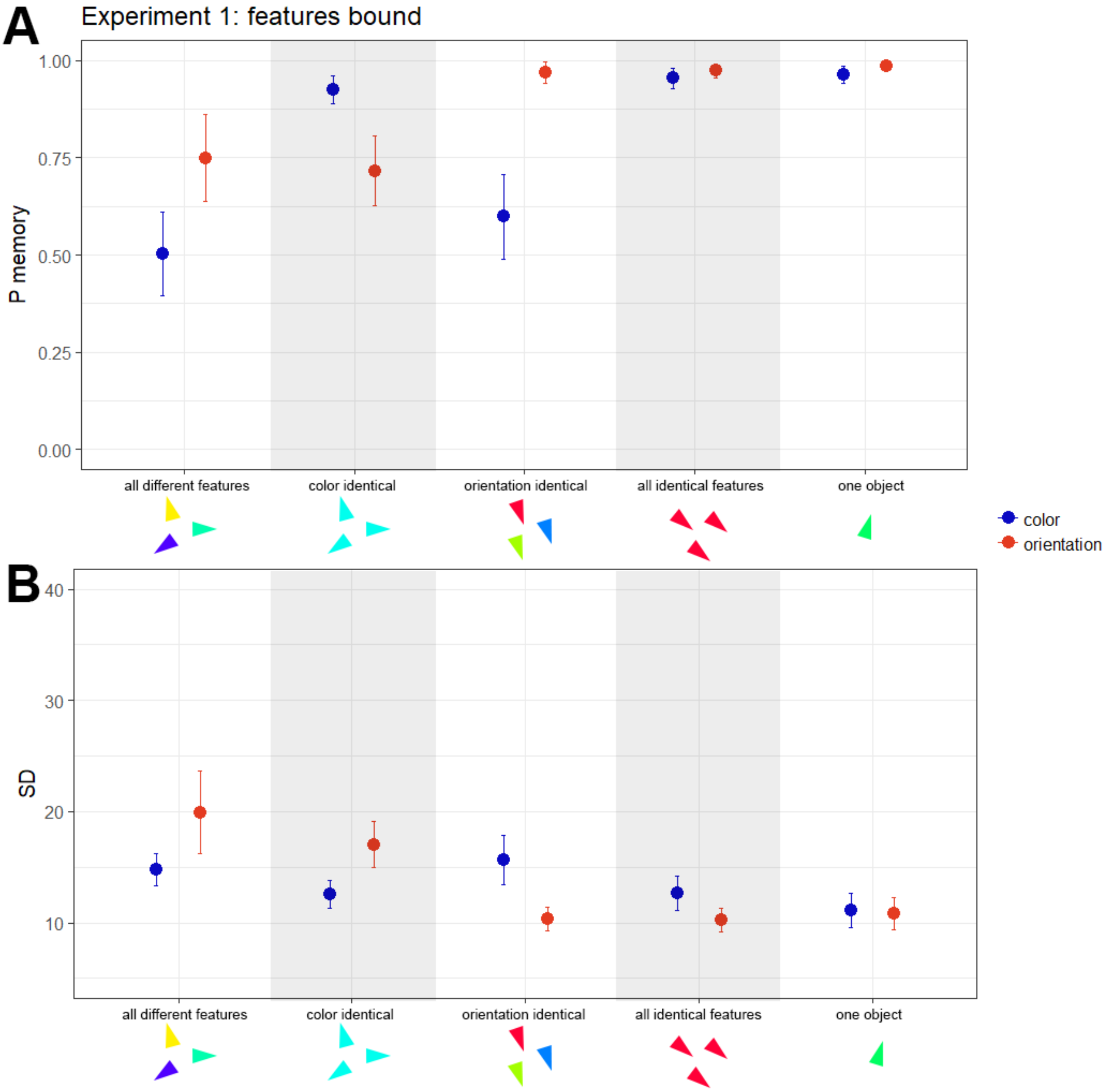

Figure 3. Results of Experiment 1: (A) P_{memory} and (B) *SD* as a function of Sample type. Error bars depict 95% CIs.

P_{memory} *for color*. We found a strong effect of Sample type on P_{memory} for color (F (4, 72) = 65.92, p < .001, η^2 = .786, $BF_{10} > 10^{20}$). P_{memory} was greater in conditions where the color was identical across objects (color identical, all features identical, and one object) compared to conditions where colors differed across (all different features and orientation identical) – t(18) >= 7.348, p < .001, Bonferroni corrected α = .005, Cohen's d >= 1.686, $BF_{10} > 10^4$. There were no significant differences between conditions with identical color across objects (color identical, all features identical, and one object) and also between conditions with different color across objects (all different features and orientation identical).

P_{memory} for orientation. We found a strong effect of Sample type on P_{memory} for orientation (F (4, 72) = 28.53, $p < .001$, $\eta^2 = .613$, $BF_{10} > 10^{10}$). P_{memory} was greater in samples where orientation was identical across objects (orientation identical, all identical features, and one object) compared to samples where orientation differed across objects (all different features and color identical) – $t(18) >= 4.537$, $p < .001$, Bonferroni corrected $\alpha = .005$, Cohen's $d >= 1.041$, $BF_{10} > 122$. There were no significant differences between conditions with identical orientation across objects (orientation identical, all identical features, and one object) and also between conditions with different orientation across objects (all different features and color identical).

SD for color. We found a strong effect of Sample type on *SD* for color (F (4, 72) = 6.115, $p < .001$, $\eta^2 = .254$, $BF_{10} = 217.3$). In all different features and in identical orientations, *SD* for color was greater compared to all identical features ($t(18) = 3.312$, $p = .0039$, Bonferroni corrected $\alpha = .005$, Cohen's $d = .760$, $BF_{10} = 11.53$) and one object ($t(18) = 3.312$, $p = .0004$, Bonferroni corrected $\alpha = .005$, Cohen's $d = 1.003$, $BF_{10} = 88.89$). In all other comparisons there were no significant differences.

SD for orientation. We found a strong effect of Sample type on *SD* for orientation (F (4, 72) = 30.66, $p < .001$, $\eta^2 = .630$, $BF_{10} > 10^{10}$). *SD* was lower in samples where orientation was the same across objects (only orientation identical, all features identical and one object) compared to conditions where orientation was different through objects (all features different and only color identical) – $t(18) >= 5.327$, $p < .001$, Bonferroni corrected $\alpha = .005$, Cohen's $d >= 1.222$, $BF_{10} > 559$. There were no significant differences between conditions with identical orientation across objects (orientation identical, all identical features, and one object) and also between conditions with different orientation across objects (all different features and color identical).

In total, in Experiment 1 we observed a consistent pattern across both probed dimensions and both estimated VWM parameters. Specifically, we found that a greater P_{memory} (roughly corresponding to capacity in items) and a lower *SD* (corresponding to better precision) take place in those clusters of conditions where the tested features have been identical across objects. More importantly, within these clusters, there were no differences there were found no effect of whether a second dimension has been represented by identical or different features. Hence, we found that both P_{memory} and *SD* for a given dimension depended only on the set size within that dimension and not on the joint set size. Additionally, we found that all identical features are encoded as efficiently as a corresponding feature in one object. Overall, the results of

Experiment 1 replicate Wang et al.'s (2017) finding in favor of independent storages for features from different dimensions.

Experiment 2

In Experiment 2, we modified stimuli so that colors and orientations belong to different spatially separated objects (exactly like in Fougnie et al., 2010). This would allow us to test whether dimension independence is preserved when there is no object-based advantage for storing the features together and when object-based load is increased.

Methods

Participants

Nineteen students from the Higher School of Economics (14 female) participated for extra course credit. They ranged in age from 18 to 22 years (average age is 18.52 years) and reported having normal or corrected to normal visual acuity, no color blindness and no neurological problems. Before the beginning of the experiment, they signed an informed consent form.

Apparatus and stimuli

Apparatus and stimuli were similar to Experiment 1, except that colors and orientations were distributed across spatially separated objects. This led to duplicated numbers of objects from Experiment 1 (from three to six and from one to two). Objects were located along an imaginary circumference with a radius of 4.35º. If there were six objects on a screen, each object was separated by 60º of rotation ±15º jitter from its neighbors (Figure 2B). When there were two objects on a screen, each object was separated by 180º of rotation from another (presented symmetrically across the center of the screen, Figure 2B). There were two types of objects depending of which dimension was relevant for memorization. "Color" objects were the circles whose colors were set using the coloring algorithm from Experiment 1. "Orientation" objects were the isosceles triangles whose orientations were set using the orientation rotation algorithm from Experiment 1. "Color" objects alternated with "orientation" objects on the imaginary circumference forming two overlapping triangular groups (this was exactly the same method of positioning as that used by Fougnie et al., 2010, Figure 2B). When two objects were presented, one was a "color" object, and another was an "orientation" object.

Procedure

The procedure of Experiment 2 was the same as in Experiment 1, except for a difference in instruction. Participants were instructed to memorize only orientations of white triangles and only colors of color circles.

Design and data analysis

Design of Experiment 2 was the same in terms of Sample types, two tested dimensions, and number of trials. The only nominal change was that the baseline “one object” condition from Experiment 1 was renamed to “two objects” for clarity (but they were equal in terms of feature set sizes). Data analysis was identical to Experiment 1.

Results and discussion

The results of the Experiment 2 for P_{memory} and *SD* are summarized on the Figure 4.

P_{memory} for color. We found an effect of Sample type on P_{memory} for color (F (4, 72) = 69.53, p < .001, η^2 = .794, $BF_{10} > 10^{20}$). P_{memory} for was greater in samples where color was identical across “color” objects (color identical, all identical features) or belonged to a single “color” object compared to samples where colors were different across objects (all different features different and orientation identical) – $t(18) >= 8.426$, $p < .001$, Bonferroni corrected α = .005, Cohen’s $d >= 1.993$, $BF_{10} > 10^6$. There were no significant differences between conditions with identical color across objects (color identical, all features identical, and single “color” object) and also between conditions with different color across objects (all different features and orientation identical). This result replicates the respective pattern from Experiment 1.

P_{memory} for orientation. We found an effect of Sample type on P_{memory} for orientation (F (4, 72) = 19.03, p < .001, η^2 = .514, $BF_{10} > 10^8$). As in Experiment 1, P_{memory} was greater in samples with all identical features or in a single “orientation” object (two objects) compared to conditions where orientations differed across objects (all different features and color identical; comparison: $t(18) >= 3.375$, $p <= .0034$, Bonferroni corrected α = .005, Cohen’s $d >= .774$, $BF_{10} > 12.981$). However, unlike Experiment 1, we found that P_{memory} for orientation suffered from the increased color set size (orientation identical condition). Specifically, P_{memory} in that condition was lower than in two other conditions with a single orientation (all identical features and two objects; comparison: $t(18) = 3.368$, $p = .0018$, Bonferroni corrected α = .005, Cohen’s $d = .842$, $BF_{10} = 22.689$), although it was greater than in the two conditions with three different orientations (all different features and color identical; comparisons: $t(18) >= 3.375$, $p <= .0034$, Bonferroni corrected α = .005, Cohen’s $d >= .774$, $BF_{10} > 12.981$). In all other comparisons there are no significant differences.

SD for color. We did not find convincing evidence for a reliable effect of Sample type on *SD* for color (F (4, 72) = 2.865, p = .029, η^2 = .137, $BF_{10} = 2.735$). We conclude, therefore, that memory set size manipulation did not have a strong effect on the precision of color encoding.

SD for orientation. We found a strong effect of Sample type on the *SD* for orientation (F (4, 72) = 71.02, p < .001, η^2 = .798, $BF_{10} > 10^{12}$). Like in Experiment 1, *SD* was lower in samples where orientations were identical across “orientation” objects (identical orientation and all identical features) or belonged to a single “orientation” object (two objects condition) compare to conditions where orientations were different across objects (all different features and identical color; comparisons: $t(18) >= 8.059$, $p < .001$, Bonferroni corrected $\alpha = .005$, Cohen's $d >= 1.849$, $BF_{10} > 10^5$). We also found that, in identical color samples (but different orientations), *SD* was smaller than in samples with all different features ($t(18) = 3.867$, $p = .0011$, Bonferroni corrected $\alpha = .005$, Cohen's $d = .887$, $BF_{10} = 33.281$), that suggests that color set size interfered with the precision of VWM for orientation. In all other comparisons, we found no significant differences.

Overall, in Experiment 2 we replicated the finding from Experiment 1 and from the literature (Fougnie et al., 2010; Wang et al., 2017; Zhang & Luck, 2008) that the set size increment within the same dimension makes P_{memory} for that dimension dropping and *SD* for that dimension raising. However, unlike Experiment 1, we also found evidence for a detrimental effect of VWM load in one dimension on feature storage in another dimension. Specifically, when orientation load was kept low but color load increased (all identical features vs. orientation identical) it impaired P_{memory} for orientations. When orientation load was high and color load increased (color identical vs. all different features) the precision of orientation estimates decreased substantially (Figure 4B). This effect was not mirrored in memory color. One possible explanation of this asymmetry could be that colors were more prioritized for encoding, so it did not suffer from overall feature load as much as less prioritized orientation memory. One finding can seemingly contradict to this interpretation, namely, the fact that P_{memory} for color drops much stronger when color set size increases than P_{memory} for orientation drops when orientation set size increases (Figure 4A). However, this fact may suggest that remembering three colors is generally a more difficult task than remembering three orientations. This suggestion does not rule out the possibility that observers put higher priority to color (note that in Experiment 1, the relative P_{memory} decrement for color was also greater despite the absence of interference between color and orientation set sizes, Figure 3A). Although this asymmetry between color and orientation needs further research, our major result indicates that there is interference between color VWM and orientation VWM when these features are distributed between different objects.

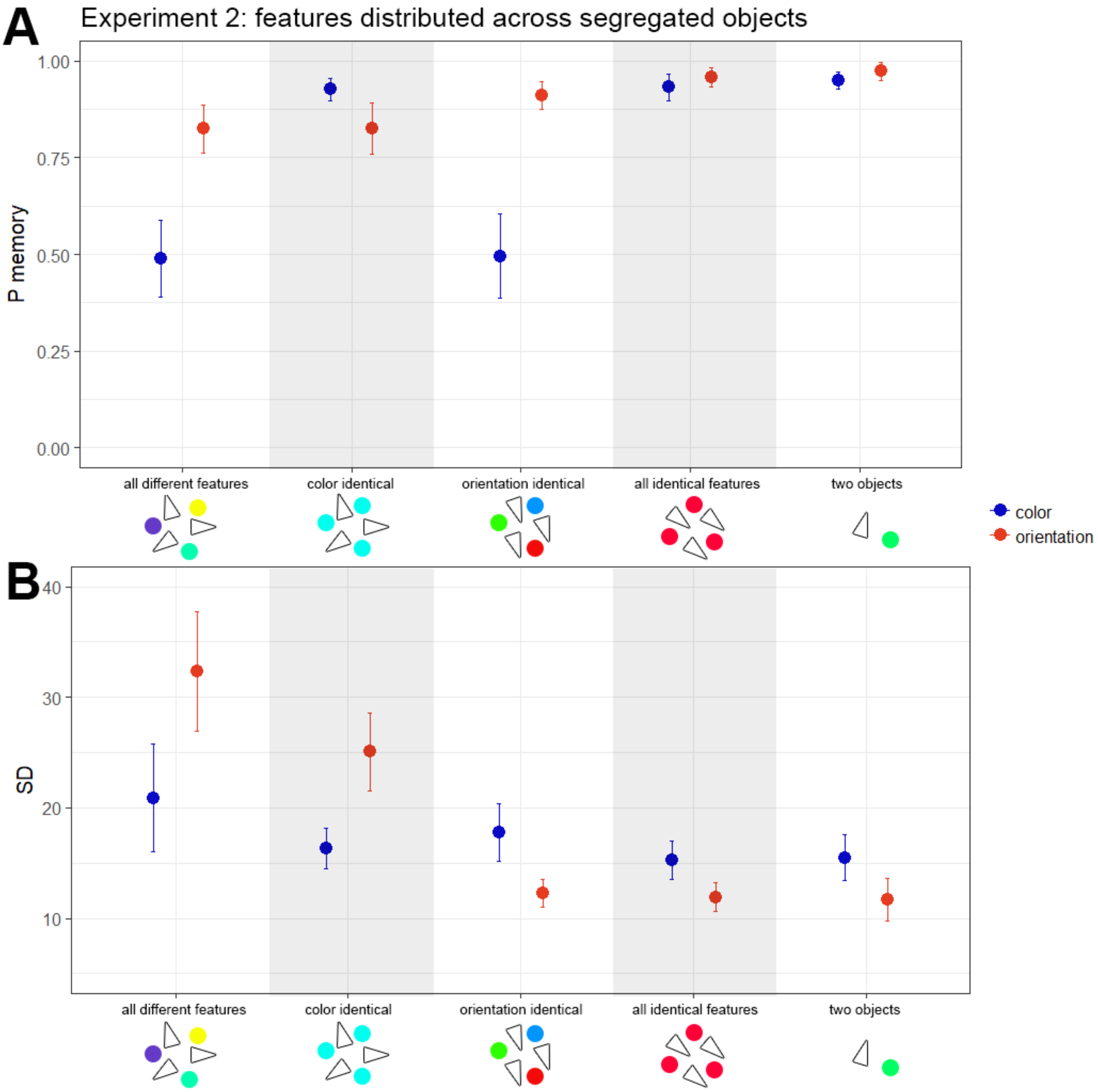

Figure 4. Results of Experiment 2: (A) P_{memory} and (B) *SD* as a function of Sample type. Error bars depict 95% CIs.

Experiment 3

The interference pattern that we found in Experiment 2 for orientation memory under the increasing color memory load, can have an alternative explanation apart from spatial separation of colors and orientations. Overall stimulus complexity was greater than in Experiment 1 that could become an extra source of noise (some items were circles, and some were triangles, some were white and some had different colors). Moreover, the instruction requiring to selectively encode different features in different objects could be also more difficult than in Experiment 1. To control for these possible confounds, we have run Experiment 3. Here, we presented participants with spatially integrated objects and asked to remember the color and orientation information about each of the object, like we did in Experiment 1. However, each of the object consisted of two overlapping parts, one corresponding to a "color" object and another corresponding to the "orientation" object from Experiment 1 (for similar manipulations, see Fougnie et al., 2010; Xu, 2002). So, each object presented in Experiment 3 had the same amount of complexity as two separate objects in Experiment 2. Also, the instruction in Experiment 3 required selective encoding of orientation information from one part of an object and of color information from another part.

Methods

Participants

Nineteen students from the Higher School of Economics (14 female) participated for extra course credits. They ranged in age from 18 to 22 years (average age is 19.03 years) and reported having normal or corrected to normal visual acuity, no color blindness and no neurological problems. Before the beginning of the experiment, they signed an informed consent form.

Apparatus, stimuli, and procedure

In general, apparatus and stimuli were the same as in two previous experiments with some differences. Each object consisted of two parts: an oriented white triangle overlaid with a color circle (see Figure 2C for examples). Object positioning was the same as in Experiment 1. The procedure was the same as in Experiment 1 with an addition that participants were instructed to remember the color of the circular part and the orientation of the triangular part of each object.

Design and data analysis were the same as in Experiment 1.

Results and discussion

The data from four participants were excluded from analysis because they showed nearly 100% guess rate in all conditions. The results of the Experiment 3 for P_{memory} and *SD* are summarized on the Figure 5.

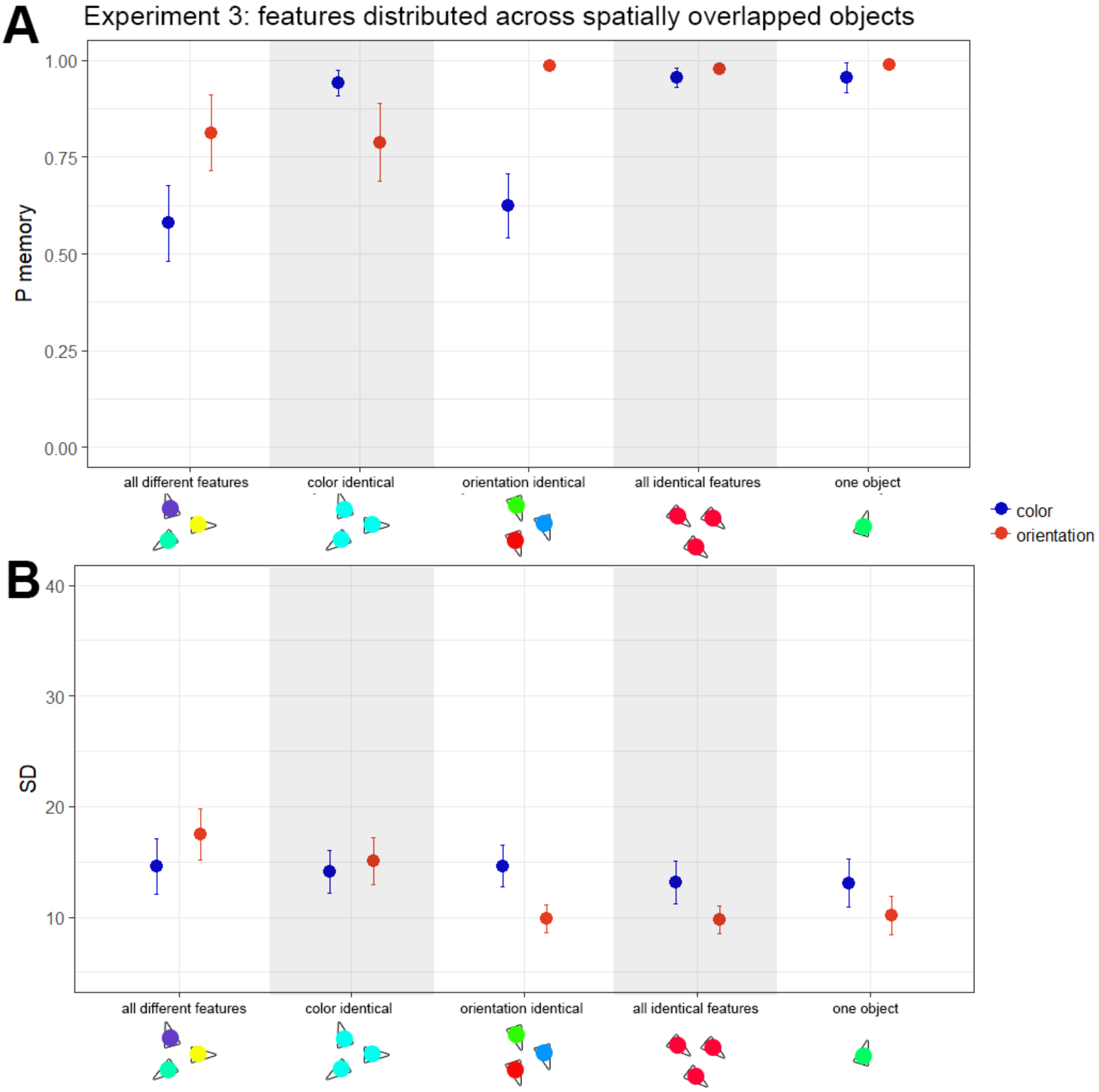

Figure 5. Results of Experiment 3: (A) P_{memory} and (B) *SD* as a function of Sample type. Error bars depict 95% CIs.

P_{memory} *for color*. We found the strong effect of Sample type on P_{memory} for color (F (4, 56) = 69.53, p < .001, η^2 = .808, $BF_{10} > 10^{20}$). P_{memory} for color was higher in all conditions where color was identical across objects (color identical, all identical features, and one object) compared to the conditions where color differed across objects (all different features and orientation identical; comparisons: $t(14) >= 7.916$, $p < .001$, Bonferroni corrected $\alpha = .005$, Cohen's $d >= 2.044$, $BF_{10} > 10^5$). In all other comparisons, we found no significant differences.

P_{memory} *for orientation*. We found the strong effect of Sample type on P_{memory} for orientation (F (4, 56) = 14.37, p < .001, η^2 = .506, $BF_{10} > 10^6$). P_{memory} was greater in all conditions where orientation was identical across objects (identical orientation, all identical features and one object) compared to the conditions where orientations differed across objects (all different features and identical color; comparisons: $t(14) >= 3.450$, $p <= .0039$, Bonferroni corrected $\alpha = .005$, Cohen's $d >= .891$, $BF_{10} > 12.18$). In all other comparisons, we found no significant differences.

SD for color. We found no effect of Sample type on the color *SD* (F (4, 56) = .726, p = .578, $\eta^2 = .049$, $BF_{10} = .139$). There were no significant differences in SD for color between conditions.

SD for orientation. We found the strong effect of Sample type on the orientation *SD* (F (4, 56) = 40.92, $p < .001$, $\eta^2 = .745$, $BF_{10} > 10^{13}$). *SD* was lower in all conditions where orientation was identical across objects (identical orientations, all identical features, and one object) compared to the conditions where orientation differed across objects (all different features and identical colors; comparisons: $t(14) >= 6.008$, $p < .001$, Bonferroni corrected α = .005, Cohen's $d >= 1.551$, $BF_{10} > 781.92$). In all other comparisons, we found no significant differences.

Therefore, the results of Experiment 3 basically replicated the principal results of Experiment 1 regarding the absence of interference between color and orientation VWM parameters. We conclude that VWM can support the independent storage of features from different dimensions in spatially integrated objects.

Comparisons between experiments

To get a more picture of feature separation vs. feature integration on VWM for both color and orientation, we directly compared the results of all three experiments. Data from 53 participants were analyzed. In Figure 6, we plotted the results of all experiments together.

There were no significant differences between experiments in P_{memory} for both colors ($F(2, 50) = 1.434$, $p = .248$, $\eta^2 = .054$, $BF_{10} =.106$) and orientations (F (2, 50) = .699, $p = .502$, $\eta^2 = .027$, $BF_{10} =.123$). Yet, these differences were substantial in SD for both color (F (2, 50) = 15.67, $p < .001$, $\eta^2 = .054$, $BF_{10} = 415$) and for orientation (F (2, 50) = 14.51, $p < .001$, $\eta^2 = .367$, $BF_{10} = 246$). These differences were provided by Experiment 2 (Figure 5B) where SD's were overall greater than in Experiment 1 (color SD: $t = 5.242$, $p < .001$, Bonferroni corrected $\alpha = .017$, Cohen's $d = .720$, $BF_{10} = 20,176$; orientation SD: $t = 4.224$, $p < .001$, Bonferroni corrected $\alpha = .017$, Cohen's $d = .580$, $BF_{10} = 218$) and Experiment 3 (color SD: $t = 4.196$, $p < .001$, Bonferroni corrected $\alpha = .017$, Cohen's $d = .576$, $BF_{10} = 213$; orientation SD: $t = 4.936$, $p < .001$, Bonferroni corrected $\alpha = .017$, Cohen's $d = .678$, $BF_{10} = 3,293$). Together these results demonstrate that both color and orientation were encoded and stored with a substantial loss in precision when they belonged to different rather than same objects. This finding is in line with the previous evidence for object-based advantage for storing features in VWM (Fougnie et al., 2010; Fougnie et al., 2013; Wheeler & Treisman, 2002).

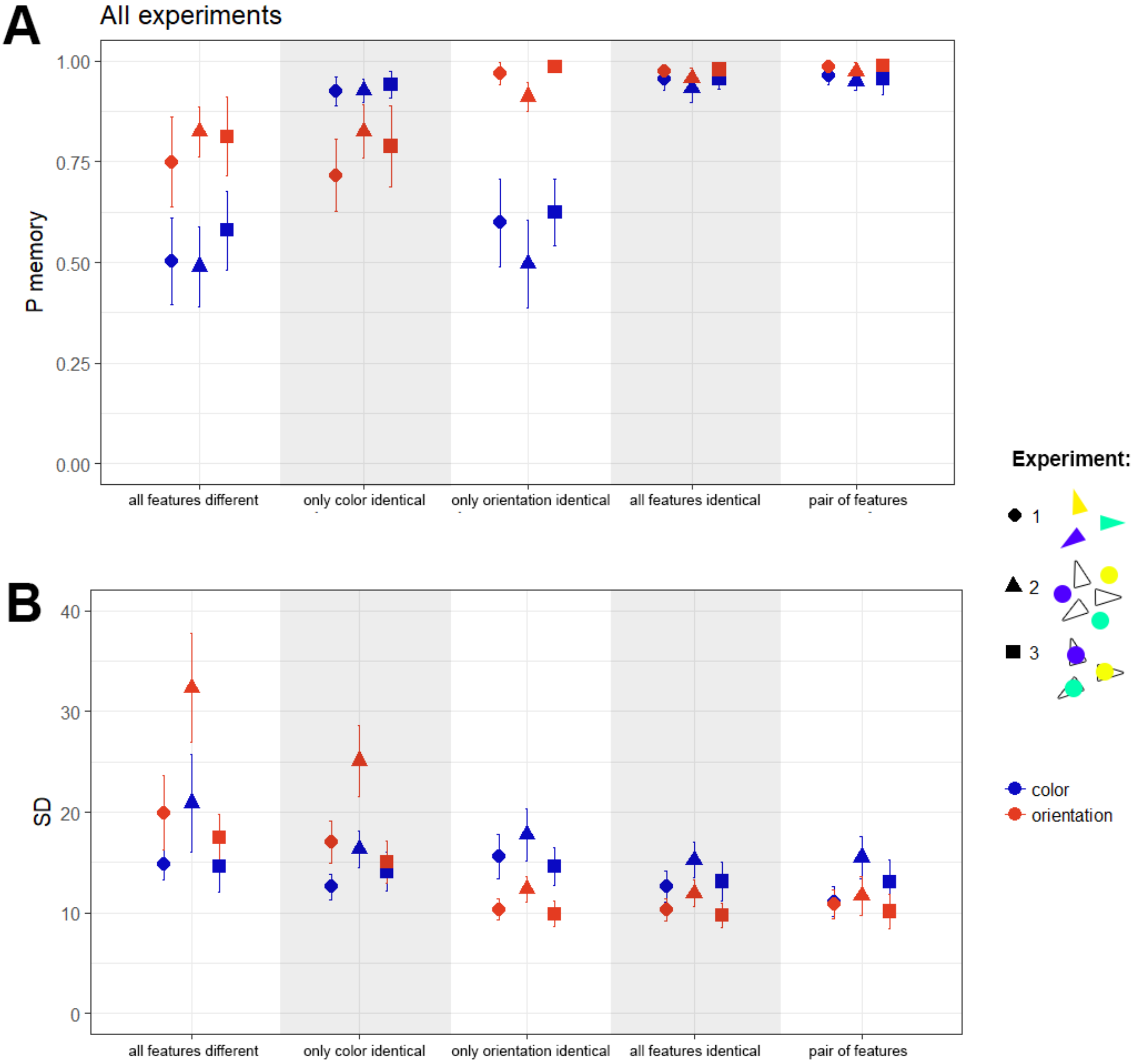

Figure 6. Results of Experiment 1-3: (A) P_{memory} and (B) *SD* as a function of Sample type and Experiment. Error bars depict 95% CIs.

General discussion

Our principal research question was about the relationship between feature-based and object-based unit organization in VWM. In particular, we tested whether the finding that features from two different dimensions, color and orientation, can be stored without substantial interference (Wang, et al., 2017; Wheeler & Treisman, 2002) is related to object-based coordination between these features. In other words, we tested whether the absence of interference is due to the fact that each particular color goes with a certain orientation within a unitary object (Duncan, 1984; Luck & Vogel, 1997). In our experiments, we implemented the same approach as Wang et al. (2017) used in their work to test independence or interdependence of VWM resources for color and orientation. This approach is based on the orthogonal manipulation with set sizes in each dimension. Our critical addition to this manipulation was spatial separation vs. spatial integration of features from different dimensions in a paradigm very much resembling that used by Fougnie et al. (2010). It is supposed that spatial separation would cause features to be perceived and encoded as belonging to different objects, whereas spatial integration would cause the features to be encoded as belonging to same objects. One could question object unity in Experiment 3 where two geometrical shapes were overlaid, but in fact spatial overlap seems to be a strong factor that aids the formation of object-like units (Rensink, 2002; Trick & Pylyshyn, 1993; Wolfe & Bennett, 1997; Xu, 2002).

Using the continuous report paradigm, we replicated the basic finding made by Wang et al. (2017) in the change detection paradigm. When colors and orientations belonged to a same set of objects (Experiments 1 and 3), we found no evidence of cross-dimensional interference. Both capacity (P_{memory}) and precision (*SD*) for colors stayed intact when the number of orientations increased, and vice versa. Together with intra-dimensional interference remarkably growing with set size, this supports the conclusion of independent capacity for features from different dimensions (Shin & Ma, 2017; Wang et al., 2017; Wheeler & Treisman, 2002). However, the pattern was different in Experiment 2 where colors and orientations were separated between different objects. Here, we found some signs of cross-dimensional interference, although they manifested only in the orientation domain. This can indicate that object separation violates the independent storage of features from different dimensions.

This pattern of results leads us to a conclusion that may seem paradoxical. On one hand, we demonstrated that features from different dimensions can be stored independently from each other. On the other hand, this independence is better supported by their belongingness to common objects. In general, this supports the idea both separate features and integrated feature "bundles" can be hierarchically stored by VWM (Brady et al., 2011; Fougnie et al., 2010, 2013) in such a way that the "bundles" facilitate the encoding and retrieval of features. Interpreting their results from the paradigm similar to our present paradigm, Wang et al. (2017) also speculated about the possibility of the hierarchically organized memories about features and objects. Our experimental manipulations with feature separation and integration provided an additional empirical support for this suggestion.

How can the object-based advantage mediate the feature independence? One possibility is that, when features are separated between different objects, observers have to spread their attention across a greater number of locations and, thus, each feature representation is noisier than when two features are integrated in one location. We did find evidence that all features in general were represented with the greater noise in Experiment 2 with feature separation (see also Fougnie et al., 2010). Viewing the noise as an important source of interference in VWM (Bays, 2015; Wilken & Ma, 2004), we could explain the cross-dimensional interference in spatially separated features by overall noisier representations. However, this explanation can be insufficient. Most importantly, it does not account for interference specificity towards a feature dimension. Therefore, structural links between individual feature representations can be important for understanding the difference between integrated and separated features. Our experiments were not devised to explore particular structures. Future theoretical analysis and following experiments would be necessary in that field to advance our understanding of VWM beyond the dichotomous "feature-based vs. object-based" scale.

Contributions

Y.A.M. designed the experiments, prepared the experimental scripts, collected and analyzed data, and wrote manuscript. N.A.T. collected and analyzed data and wrote manuscript. I.S.U. conceptualized the basic ideas, designed the experiments and wrote manuscript.

References

Alvarez, G. A., & Cavanagh, P. (2004). The capacity of visual short-term memory is set both by visual information load and by number of objects. *Psychological Science: A Journal of the American Psychological Society / APS*, *15*(2), 106–111. https://doi.org/10.1167/2.7.273

Baddeley, A. D. & Hitch, G. J. (1974). Working memory. In G. A. Bower (ed). *The Psychology of Learning and Motivation: Advances in Research and Theory*, pp. 47–89. New York: Academic.

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

Bays, P. M. (2015). Spikes not slots: Noise in neural populations limits working memory. *Trends in Cognitive Sciences*, *19*(8), 431–438. https://doi.org/10.1016/j.tics.2015.06.004

Bays, P. M., Catalao, R. F. G., & Husain, M. (2009). The precision of visual working memory is set by allocation of a shared resource. *Journal of Vision*, *9*(10), 7–7. http://doi.org/10.1167/9.10.7

Brady, T. F., & Alvarez, G. A. (2011). Hierarchical encoding in visual working memory: Ensemble statistics bias memory for individual items. *Psychological Science*, *22*(3), 384–392. https://doi.org/10.1177/0956797610397956

Brady, T. F., Konkle, T., & Alvarez, G. A. (2011). A review of visual memory capacity: Beyond individual items and toward structured representations. *Journal of Vision*, *11*(5), 4–4. https://doi.org/10.1167/11.5.4

Brown, L. A., & Brockmole, J. R. (2010). The role of attention in binding visual features in working memory: Evidence from cognitive ageing. *The Quarterly Journal of Experimental Psychology*, *63*(10), 2067–2079. https://doi.org/10.1080/17470211003721675

Cowan, N. (2001). The magical number 4 in short term memory. A reconsideration of storage capacity. *Behavioral and Brain Sciences,* *24*(4), 87–186. https://doi.org/10.1017/S0140525X01003922

Cowan, N., Chen, Z., & Rouder, J. N. (2004). Constant capacity in an immediate serial-recall task: A logical sequel to Miller (1956). *Psychological Science*, *15*(9), 634–640. https://doi.org/10.1111/j.0956-7976.2004.00732.x

Duncan, J. (1984). Selective attention and the organization of visual information. *Journal of Experimental Psychology: General, 113*(4), 501–517. https://doi.org/10.1037/0096-3445.113.4.501

Fougnie, D., & Marois, R. (2009). Attentive tracking disrupts feature binding in visual working memory. *Visual Cognition*, *17*(1–2), 48–66. https://doi.org/10.1080/13506280802281337

Fougnie, D., Asplund, C. L., & Marois, R. (2010). What are the units of storage in visual working memory? *Journal of Vision*, *10*(12), 27–27. https://doi.org/10.1167/10.12.27

JASP Team (2018). JASP (Version 0.9.0.0) [Computer software]

Jeffreys, H. (1961). *Theory of Probability (3rd ed.)*. Oxford: Oxford University Press.

Kahneman, D., Treisman, A., & Gibbs, B. J. (1992). The reviewing of object files: object-specific integration of information. *Cognitive Psychology*, *24*(2), 175–219. https://doi.org/10.1016/0010-0285(92)90007-O

Lee, D., & Chun, M. M. (2001). What are the units of visual short-term memory, objects or spatial locations? *Perception & Psychophysics*, *63*(2), 253–257. https://doi.org/10.3758/BF03194466

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279–281. https://doi.org/10.1038/36846

Luria, R., & Vogel, E. K. (2011). Shape and color conjunction stimuli are represented as bound objects in visual working memory. *Neuropsychologia*, *49*(6), 1632–1639. https://doi.org/10.1016/j.neuropsychologia.2010.11.031

Miller, G. A. (1956). The magical number seven, plus or minus two: some limits on our capacity for processing information. *Psychological Review, 101*(2), 343–352. https://doi.org/10.1037/h0043158

Olson, I. R., & Jiang, Y. (2002). Is visual short-term memory object based? Rejection of the “strong-object” hypothesis. *Perception and Psychophysics*, *64*(7), 1055–1067. https://doi.org/10.3758/BF03194756

Pertzov, Y., Dong, M. Y., Peich, M. C., & Husain, M. (2012). Forgetting what was where: the fragility of object-location binding. *PLoS ONE*, *7*(10). http://doi.org/10.1371/journal.pone.0048214

Phillips, W. A. (1974). On the distinction between sensory storage and short-term visual memory. *Perception & Psychophysics*, *16*(2), 283–290. https://doi.org/10.3758/BF03203943

Pierce, J. W. (2007). PsychoPy - psychophysics software in Python. *Journal of Neuroscience Methods, 162,* 8-1.

Rensink, R. A. (2000). The dynamic representation of scenes. *Visual Cognition*, *7*(1–3), 17–42. https://doi.org/10.1080/135062800394667

Rouder, J. N., Speckman P. L., Sun D., Morey R. D., & Iverson G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review*, 16(2), 225-237. doi:10.3758/PBR.16.2.225.

Shin, H., & Ma, W. J. (2017). Visual short-term memory for oriented, colored objects. *Journal of Vision*, *17*(9), 1–19. https://doi.org/10.1167/17.9.12

Suchow, J. W., Brady, T. F., Fougnie, D., & Alvarez, G. A. (2013). Modeling visual working memory with the {MemToolbox}. *Journal of Vision*, *13*(10), 9. https://doi.org/10.1167/13.10.9

Trick, L. M., & Pylyshyn, Z. W. (1993). What Enumeration Studies Can Show Us About Spatial Attention: Evidence for Limited Capacity Preattentive Processing. *Journal of Experimental Psychology: Human Perception and Performance,* *19*(2), 331–351. https://doi.org/10.1037/0096-1523.19.2.331

Treisman, A. (1999). Solutions to the binding problem: Progress through controversy and convergence. *Neuron*, *24*(1), 105–110. https://doi.org/10.1016/S0896-6273(00)80826-0

Vogel, E. K., Woodman, G. F., & Luck, S. J. (2001). Storage of features, conjunctions and objects in visual working memory. *J Exp Psychol Hum Percept Perform*, *27*(1), 92–114. https://doi.org/10.1037//0096-1523.27.1.92

Wagenmakers, E.-J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Selker, R., Gronau, Q. F.,Dropmann, D., Boutin, B., Meerhoff, F., Knight, P., Raj, A., van Kesteren, E.-J., van Doorn, J., Šmíra, M., Epskamp, S., Etz, A., Matzke, D., de Jong, T., van den Bergh, D., Sarafoglou, A., Steingroever, H., Derks, K., Rouder, J. N., Morey, R. D. (2017). Bayesian inference for psychology. Part II: Example applications with JASP. *Psychonomic Bulletin & Review*, 1–19. http://doi.org/10.3758/s13423-017-1323-7

Wang, B., Cao, X., Theeuwes, J., Olivers, C. N. L., & Wang, Z. (2017). Separate capacities for storing different features in visual working memory. *Journal of Experimental Psychology:*

Learning, Memory, and Cognition, *43*(2), 226–236. https://doi.org/10.1037/xlm0000295

Wheeler, M. E., & Treisman, A. M. (2002). Binding in short-term visual memory. *Journal of Experimental Psychology. General*, *131*(1), 48–64. https://doi.org/10.1037//0096-3445.131.1.48

Wilken, P., & Ma, W. J. (2004). A detection theory account of change detection. *Journal of Vision*, *4*(12), 11–11. https://doi.org/10.1167/4.12.11

Wolfe, J. M., & Bennett, S. C. (1997). Preattentive object files: Shapeless bundles of basic features. *Vision Research*, *37*(1), 25–43. https://doi.org/10.1016/S0042-6989(96)00111-3

Xu, Y. (2002). Encoding color and shape from different parts of an object in visual short-term memory. *Perception & Psychophysics*, *64*(8), 1260–1280. https://doi.org/10.3758/BF03194770

Xu, Y., & Chun, M. M. (2006). Dissociable neural mechanisms supporting visual short-term memory for objects. *Nature*, *440*(7080), 91–95. https://doi.org/10.1038/nature04262

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*(7192), 233–235. https://doi.org/10.1038/nature06860

Yuri A. Markov
National Research University Higher School of Economics (Moscow, Russia). “Laboratory for Cognitive Research”. Research Assistant;
E-mail: yuamarkov@gmail.com

Any opinions or claims contained in this Working Paper do not necessarily reflect the views of HSE.

© Markov, Tiurina, Utochkin, 2018