Flexible Resources in Visual Working Memory for Color, Size, and Orientation

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Abstract

Visual working memory (VWM), as the functional unit to temporarily store visual information, has been mainly viewed from the perspectives of two opposing classes of models. Firstly, the integrated object perspective, which supports a discrete capacity limit on the object level, and secondly, the feature binding models according to which VWM resources are more flexible and continuous on the feature dimension level. Recent activity in the field challenged the validity of memory precision measures of feature-based approaches. This motivated the current study to conduct the main VWM task with individualized sets of stimuli, which were identified in a pre-experimental phase in the form of six discriminable feature values for each feature dimension (color, size, and orientation). Results of the main VWM task confirm the significant impact of the number of presented stimuli and the attentional instructions on memory precision, which both argue against the integrated object perspective. More so, the results fit a conceptualization of VWM with flexible feature resources that tend to be reallocated to the more difficult memory subjects, e.g., the less discriminative object feature at the cost of the more discriminative features. The current findings show the relevance of attention and individual differences in perception within the research of VWM. This requires future research to differentiate human VWM performance and measures for VWM resource limits according to these qualitative dimensions.

Keywords: *Visual working memory, Short-term memory resources, Memory precision, Attention, Perception*

Introduction

With the rising interest in understanding and modeling cognitive processes, substantial research has been dedicated to the specific field of binding features of an object in visual working memory (VWM). The way we perceive objects and sceneries in real life is a complex conjunction of single features among which are color, size, and orientation. In order to reliably recall such sceneries, an internal representation of objects and their unique features has to be formed in VWM. Recognizing the traditional and profound understanding of human's working memory with a resource capacity limit by Miller (Miller, 1956) and Cowan (Cowan, 2001), an initial question arises. Is a resource limit applied to an amount of different integrated objects with several features, or rather to features that may have independent resource pools and thus independent capacities? This was a complex debate and several distinct theoretical frameworks were established on the basis of empirical research, among which a non-binary framework of VWM that recognized qualitative dimensions of memory rather than discrete capacity limits (Schneegans & Bays, 2018).

The early influential work by Luck and Vogel (Luck & Vogel, 1997; Vogel, Woodman, & Luck, 2001) and Fukuda, Awh, and Vogel (2010) have supported the understanding of object binding as units in VWM that store integrated object representations rather than single features. Concretely, this conclusion was based on behavioural data in change detection tasks that showed that there was no significant difference in performance when retaining objects with four different features or a single feature, allowing in total sixteen individual features to be retained. While these findings are coherent with Cowan's defined working memory capacity of four units (Cowan, 2001), several studies after Luck and Vogel failed to replicate these findings, challenging the theoretical modeling of object binding in the form of object slots (Delvenne & Bruyer, 2004; Wheeler & Treisman, 2002; Xu, 2002).

Especially Wheeler and Treisman (2002) and later, Wang, Cao, Theeuwes, Olivers, and Wang (2017), suggest from their findings the opposing theoretical framework, namely that individual capacities exist for each feature dimension. Their behavioural data in change detection tasks similar to Luck and Vogel's showed that features could be added in one dimension without negatively impacting the recall performance of another dimension, using colored objects with location or shape, and objects with orientation and color, respectively. Furthermore, Wheeler and Treisman (2002) proposed a model of object binding that acknowledges the impact of attention, in which VWM capacity "is limited both by the independent capacity of simple feature stores and by demands on attention networks that integrate this distributed information into complex but unified thought objects" (Wheeler & Treisman, 2002, p. 48). While the prior integrated object model does not support influences on memory performance by attentional instructions, the latter independent feature model sees a clear benefit on attended features (Park, Sy, Hong, & Tong, 2017; Verghese, 2001).

As substantial evidence exists for both theoretical models, one should consider viewing them as mutually inclusive. On the basis of recent empirical and neuroimaging findings, Fougnie and Alvarez (2011) proposed a hierarchical structure of VWM, that at the bottom level, stores and forgets features independently, and at the top level, can form integrated feature bundles (Brady, Konkle, & Alvarez, 2011; Fougnie & Alvarez, 2011; Harrison & Tong, 2009; Markov, Tiurina, & Utochkin, 2019; Serences, Ester, Vogel, & Awh, 2009). In earlier work, Kahneman, Treisman, and Gibbs (1992) already suggested a model called “object files” in order to abstract that features are individually represented in VWM, but clustered in bound units.

Consistent with the above, the term “object benefit” has been introduced by Schneegans and Bays (2018), stressing that various studies found that the “object benefit (or, conversely, the cost of memorizing additional features of a stimulus) depends on the distance and connectedness of the individual features within the object” (Schneegans & Bays, 2018, p. 5). This framework allows to additionally emphasize the importance of distinctiveness within a feature as an advantage, meaning that information stored in VWM can be categorized, in the form of verbalisation of a color or relating orientations to a clock representation (Donkin, Nosofsky, Gold, & Shiffrin, 2015; Brown & Wesley, 2013). Oberauer et al. (2018) further claimed that previous experiments, that support strong object representations in VWM with a discrete capacity limit, might have missed the effect of memory precision as easily discriminative features could have been detected even with reduced memory precision.

Furthermore, recent experiments challenge the assumption of a discrete resource limit in VWM. Concretely, the findings by Ma, Husain, and Bays (2014), Park et al. (2017), and Wilken and Ma (2004) provide evidence that VWM has a flexible precision and memory noise can vary on a continuum. This model clearly suggests that the feature representations in VWM gradually become noisier with an increasing number of features. Overall, by acknowledging independent and integrable feature bindings as well as qualitative dimensions of memory, Oberauer et al. (2018) summarise VWM capacity to be limited by at least three dimensions: the number of objects, the number of features per object, and the memory precision for each feature.

The qualitative understanding of VWM impacts the approaches to be taken in empirical research to monitor individuals’ performance. Therefore, delayed estimation paradigms rather suit the measurability of VWM precision (Wilken & Ma, 2004), compared to binary change detection tasks (e.g., Luck & Vogel, 1997). However, measuring, for instance, a to-be-recalled color with a standard color wheel that entails constant differences between gradients, fails to account for individual sensitivity levels to distinguish certain features (Webster, Miyahara, Malkoc, & Raker, 2000).

In the current experiment, objects were used that vary along three dimensions: color, size, and orientation, which exceeds the dimensions primarily used in previous studies (Fougnie, Asplund, & Marois, 2010; Wang et al., 2017; Markov et al., 2019). Furthermore, the goal was to make use of just distinguishable visual features and therefore, decrease the object benefit and allow increased validity on feature binding in VWM. In order to avoid that the VWM task displays different object features that the individual participant cannot visually distinguish, a pre-experimental stimulus selection was employed. In this pre-experimental phase, each participant engaged in a change detection task for each feature dimension to create a set of four reliably distinguishable feature values. In line with the implications of memory precision, the main VWM task was designed as a delayed estimation task with six answer options to choose from. The distances between the different answer options were based on the feature sets from the pre-experimental phase in addition to two extreme answer options.

Aim of the Study

The aim of the present study was to explore to what extent the recall precision of multi-feature objects is affected by attentional instruction (attend to either color, size, orientation, or all) and set size (one, two, or four objects). On the basis of the feature-based models, it was assumed that participants` memory precision decreases with increasing set size. It was especially interesting to observe whether the precision in recall is already impacted with a memory load less than a capacity limit of four on the feature level. The latter would suggest that the initial independent feature binding model cannot be applied as it predicts no substantial cost when the capacity limit of four is not exceeded per feature. Additionally, the attention condition was assumed to significantly reduce memory precision if all features had to be recalled, which is a supported effect by the independent feature and the hierarchical model. In the line of reasoning of the hierarchical model, the latter effect would not be substantial if the answer options were highly discriminative and therefore easier to bundle features to recall. According to the integrated object model, none of the effects above would be observed.

Methods

Participants

Twenty students from the age of 19 to 28 participated (M_{age} = 22.5; range: 18-28 yrs; 12 Female; 8 Male; 10 German, 6 Dutch, 2 Korean, 1 American, 1 Chinese; 15 right-handed, 4 left-handed, 1 ambidexter). All of the participants reported normal color vision, which was confirmed with an application called “Color blind test”, using “Ishihara 38 Plates”, and all had normal or corrected to normal visual acuity, which was tested with an application called “LooC”, using Landolt C stimuli

(Bach, 2007). The experiment was approved by the Faculty of Behavioural, Management and Social Sciences ethics committee of the University of Twente and all participants provided written informed consent.

Materials

The preliminary tests including the above mentioned color vision and visual acuity tests, as well as the handedness survey by Annet (1970), were performed on an Ipad. Stimulus presentation and data collection were performed using PyCharm 2020.2.1 development environment for Python 3.8 on a laptop running MacOS. All parts of the experiment were presented from a viewing distance of 60-90 cm on a 13-inch screen, with 1200 by 800 pixel resolution and a white background. Furthermore, different materials were used to elevate the laptop in order to ensure a consistent eyes-screen angle across all participants.

Experimental Design

The stimuli used were rectangles with a range in size between 90x30 and 246x69 in pixels, a range in color between 190 and 288 hue degrees, and a range of orientation between 20 and 86 degrees. Due to the individual stimulus selection, the starting values of the relevant feature and thus, the lower limit of the value range was equal across all participants, while the upper limit varied drastically between individuals. When applicable, the non-relevant features were set to a default at size (90x30), at color (dark grey), or at orientation (90 degrees). In the main VWM task, answer options were constructed with the four relevant feature values and two extremes, calculated by subtracting or adding twice the first or last feature difference, respectively. For the Size feature, a default minimum and maximum (50x16; 250x83, respectively) had to be installed as this condition easily reached either negative values or exceeded the screen size.

Pre-Experimental Stimulus Selection

The individual stimulus selection served the purpose to ensure that the stimuli used in the main VWM experiment are reliably distinguishable. This unique approach has only been implemented once before (Miežytė, 2019) and several points of improvement were addressed in the experiment design in this study. As the stimulus selection was not supposed to be a VWM task in itself but a perceptual task, the stimuli pair was presented next to each other simultaneously rather than after each other. Furthermore, it had to be addressed that a binary change detection involves response bias and humans might respond more often that they detect a difference in cases of uncertainty. Therefore, control trials that displayed equal stimuli had to be correctly responded to twice in addition to three trials of the different stimuli pair in order for two stimuli values to be saved as reliably distinguishable. Figure 1 displays exemplary stimulus pairs for each feature dimension. In total, participants had to do the pre-experimental test until four discrete stimuli were identified.

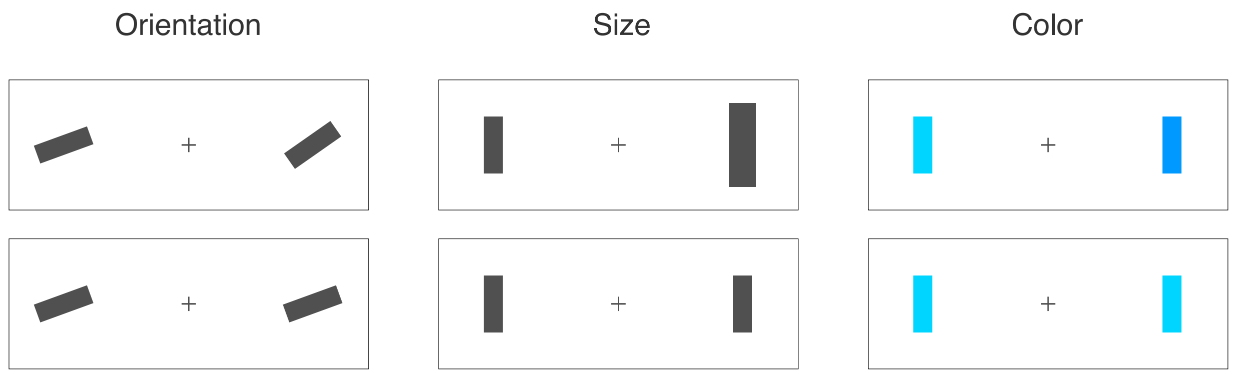

Figure 1. The top row displays exemplary pre-experimental stimuli pairs to distinguish. The bottom row shows the corresponding control trials to report equality.

Main Experiment

During this phase, several different trial combinations were installed as variations of VWM tasks. Firstly, the attention condition was displayed, followed by the stimuli display. The attention condition varied in four blocks, either focused attention *color, size,* or *orientation*, or divided attention *all*. The stimuli display varied in set size of either one, two, or four rectangles, consisting of the feature values identified in the pre-experimental phase. The focused attention condition made use of random values from the individual relevant feature values and the default values for the non-relevant features, while the divided attention condition made use of random combinations of all individual features values. After the stimuli display, a grey circle of 45 mm radius appeared at one randomly chosen target that indicated the rectangle to be recalled and chosen from the following presented six answer options (Figure 2). Overall, each attention block was presented five times, consisting of three times each set size in the focused attention conditions. In the divided condition, each feature was asked to be recalled five times for each set size in a randomized order over the whole course of five block iterations. After three block iterations, a break was installed for participants to briefly rest their eyes.

During the design process, the location of stimuli was subject to standardization as spatial implications can majorly influence VWM precision. Therefore, the fixation cross was centered and the stimuli were always displayed on a peripheral circle of a 200 mm radius around the center.

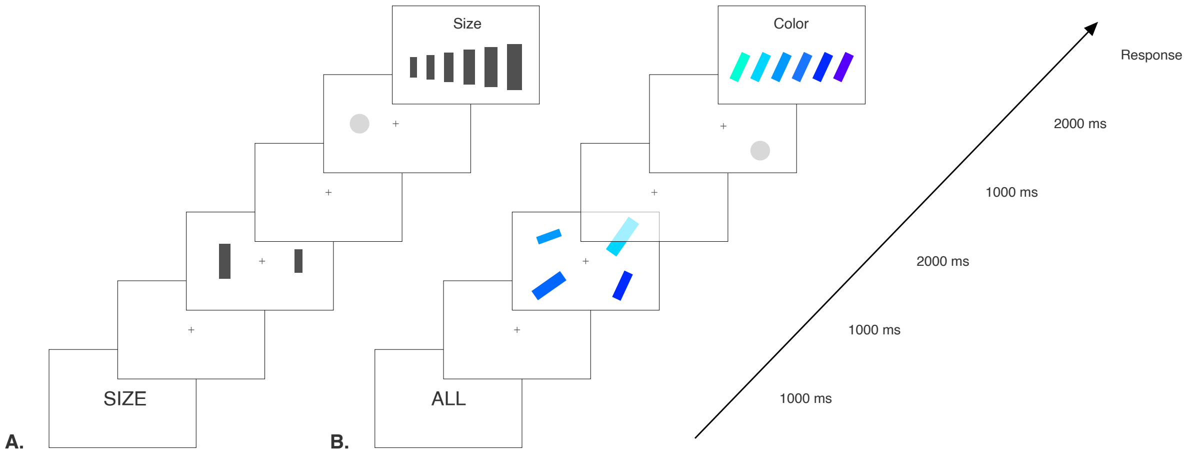

Figure 2. Example trials and sequence of the main VWM task. A. displays a focused attention trial of set size two with the feature size. B. shows a divided attention trial of set size four with the feature color.

Procedure

After the preliminary tests of color vision, visual acuity, and handedness survey (Annet, 1970), the participants received written instructions for the two experimental phases. For both phases, participants conducted sample practice trials of every condition in order to get familiar with the application.

In the first phase, they completed the sensitivity test in order to determine the individual set consisting of the four most distinguishable colors, sizes, and orientations. Hereby, the experimenter recognized with the first participant that they repeatedly answered the control equal stimuli pair to be different, which would evoke an infinite pre-experimentation phase because of incorrect false-positive responses. Therefore, the experimenter decided to add further verbal instructions, namely to take a more conservative approach when responding that stimuli are different. The experimenter further reassured the participants that among the trials, there existed quite some equal stimuli trials, trying to reduce the response bias wanting to detect the smallest differences. Except for the first participant, these verbal instructions were added after reading the written instructions. Overall, the pre-experimental phase approximately lasted 6 to 9 minutes.

In the second phase, participants completed the main experimental VWM task in two sessions of approximately 15 and 10 minutes, consisting of 180 trials in total (108 and 72, respectively). During the practice trial, the experimenter stressed the importance to reduce their eye movements and thus, proposed the strategy to blink after the response selection in order to recenter their vision on the fixation cross.

Statistical approaches

Data preparation was performed with Python 3.8 and the final data analysis was performed with RStudio Version 1.4.1103. Descriptive statistics were performed on the pre-experimental stimulus selection data. Furthermore, participants were given a ranking score per feature, based on the absolute difference between their first and fourth individual feature value.

Regarding the main experimental phase, each trial response was coded as an integer error distance (ED) between the target feature value and the chosen feature value out of the six answer options. Thus, EDs were able to vary from 0 to 5. Two types of analyses were performed on the main experiment data:

i. One sample t-tests were performed in order to check whether the mean ED for all 18 trial combinations differed from chance. Hereby, the EDs were tested both against the average distance value of six answers ((2.5+1.83+1.5+1.5+1.83+2.5)/6 = 1.94), as well as the average distance value of four answers ((1.5+1+1+1.5)/4 = 1.25), as some participants reported that they inferred quickly that the outer two extreme answer options never occurred.
ii. One repeated measures Anova was performed in order to check the effects of Attention Condition, Feature, and Set Size on the task performance. Attention Condition was an independent variable (IV) of two levels. While the first level, focused attention, included the color, size and orientation instructions, the second level, divided attention, represented the all instruction. The IV Feature referred to the feature been asked to remember from the answer options, either color, size or orientation. The third IV Set Size varied between one, two, or four presented stimuli. The continuous dependent variable was the average ED for each of the 18 trial combinations per participant. Thus, a 3 (Feature) x 3 (Set Size) x 2 (Attention) repeated measures Anova design was employed. In order to receive insights into comparisons between conditions, Bonferroni-corrected pairwise t-tests were performed.

Results

Pre-Experimental Phase

Descriptive statistics were conducted in order to gain insights in the subjective ability to discriminate within all three feature dimensions. Figure 3 displays the total distance between the lowest and highest personally selected values on a physical scale (color hue and orientation in degrees and size in x-value of pixel-ratio). The displayed plot (Figure 3) demonstrates the large individual differences of participant's ability to distinguish an object's color, size, or orientation. The performance varied the most for size and color (M = 85, SD = 35.1; M = 61.7, SD = 24.1), while the orientation total distances were more similar across all participants (M = 36.7; SD = 13.5). The assigned rankings of feature distances between participants revealed that Participant 1 did not have systematically different feature distances than others. Thus, the data of Participant 1 were included in further analyses.

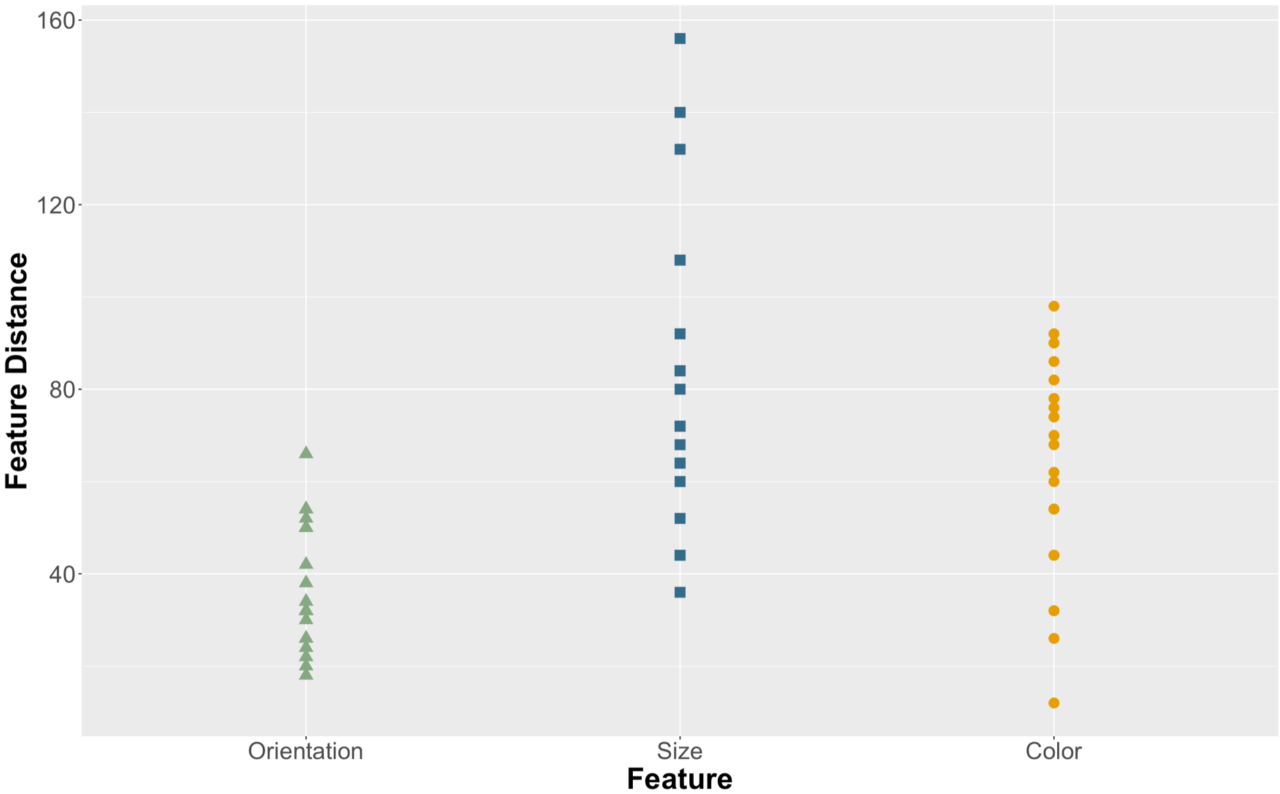

Figure 3. Feature distance, the absolute difference between participants' first and fourth individual feature value, for each feature. Feature values for orientation and color (hue) were quantified in degrees, whereas feature values for size were quantified by the x-value of the stimulus' pixel ratio. The lower the feature distance the higher the sensitivity to distinguish within the corresponding feature dimension.

Main Experimental Phase

Guessing Behaviour

The one-sample t-tests revealed that the ED of each of the 18 different trial combinations was significantly lower than the average distance value of six answer options (1.94; $-49.1 < t(19) < -23.3$, $p < 0.001$). The largest divergence from chance was observed in the color condition with two stimuli, $M_{diff} = -1.73$, $t(19) = -37.9$, $p < 0.001$ (95% confidence interval (CI): [-1.82, -1.63]), while the smallest difference was observed in the orientation condition with four stimuli, $M_{diff} = -1.20$, $t(19) = -25.6$, $p < 0.001$, CI: [-1.30, -1.10]. Even when considering the guessing behaviour of only four answer options, the ED in every condition was significantly lower than the average distance value (1.25; $-27.8 < t(19) < -10.9$, $p < 0.001$). All results above indicate that participants were not guessing in the main experimental task in none of the conditions (Figure 4).

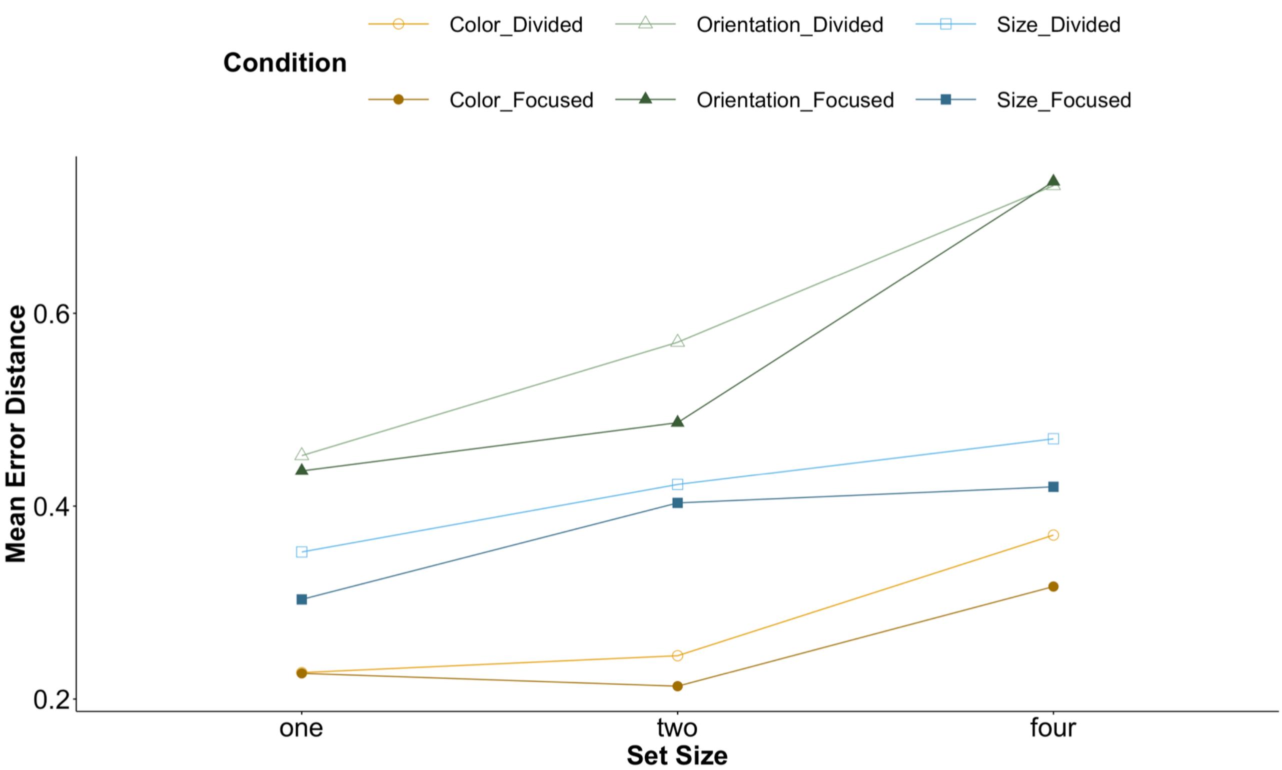

Figure 4. The mean ED as a function of set size in all combinatorial feature/attention conditions. The lower the mean ED, the higher the memory precision in the corresponding condition.

Repeated Measures Anova

All assumptions were met for the following statistical analyses after the removal of two data points that were identified as extreme outliers.

Regarding the initial repeated measures Anova, the main effect of Attention Condition on ED was significant, $F(1, 19) = 25.9$, $p < 0.001$, $\eta_p 2 = 0.58$. ED was smaller in the focused attention conditions in which only one object feature had to be remembered (0.39; CI: [0.36, 0.43]) than in the divided attention conditions wherein either of the three object features could be relevant and had to be remembered (0.43 CI: [0.39, 0.46]; see Figure 4). The main effect of Feature was also significant, $F(2, 38) = 19.60$, $p < 0.001$, $\eta_p 2 = 0.51$. ED was smallest in color trials (0.27, CI: [0.23, 0.31]), intermediate for size trials (0.40, CI: [0.36, 0.44]) and largest when orientation had to be remembered (0.57; CI: [0.53, 0.61]). Set Size also had a major effect on ED, $F(2, 38) = 20.33$, $p < 0.001$, $\eta_p 2 = 0.52$, where one stimulus reported the smallest ED (0.33, CI: [0.29, 0.38]), two stimuli reported a slightly larger ED (0.39, CI: [0.35, 0.43]), and four stimuli evoking the largest EDs (0.51, CI: [0.46, 0.55]). Lastly, a significant interaction between Feature and Set Size was found ($F(4, 76) = 3.87$, $p < 0.01$, $\eta_p 2 = 0.17$) and the interaction between all factors revealed significant ($F(4, 76) = 4.32$, $p < 0.01$, $\eta_p 2 = 0.19$).

Bonferroni-corrected pairwise comparisons showed that every level differed significantly within their main factor (p < 0.01). When differentiating the interaction effect of Feature and Set Size per Attention Condition, EDs in none of the conditions differed significantly between the presentation of one or two stimuli (p > 0.05). It further revealed that the divided attention instruction highly impacted the increase of ED of color trials from one to four stimuli, t(19) = -3.25, p = 0.01, compared to the focused condition in which presenting one or four stimuli did not significantly increase the EDs (p > 0.05). Comparing the two attentional instructions in all conditions revealed that with the set size of one, only size trials were significantly smaller in the focussed attention compared to the divided attention (t(19) = - 3.75, p = 0.001). With the set size of two, the ED was significantly increased for orientation (O) and color (C) trials (O: t(19) = -3.65, p = 0.002; C: t(19) = -2.46, p = 0.023). Lastly, size (S) and color (C) trials of set size four significantly differed between the two attentional instructions (S: t(19) = -3.02, p = 0.007; C: t(19) = -2.37, p = 0.029).

In summary, presenting one or two stimuli in both attention conditions did not influence the task performance of any relevant feature. Especially with the feature color, the divided attention instruction highly impacted the increase of ED from one to four stimuli, compared to the focused condition in which presenting one or four stimuli did not significantly differ. The negative effect of divided attention compared to the identical focussed trial was significant when one stimulus was presented with size being the relevant feature. The same effect applied to the set size of two when orientation or color had to be remembered, and with the set size of four when size and color had to be remembered.

Discussion

The current study aimed to explore the memory precision of multi-feature objects under the influence of attentional instructions and across different set sizes. While the integrated object model suggests that an object is represented in VWM as one unit and VWM is restricted by a discrete capacity limit, the independent feature model suggests resource pools for every feature dimension. The latter feature model can be differentiated by the notion of memory precision rather than a cut-off capacity limit and by the impact of attentional instructions. A last model combines the two opposing frameworks in the form of a hierarchical structure of VWM.

In contrast to many VWM experiments conducted before, this study implemented a pre-experimental phase in which participants' individual perceptual performance determined the stimuli to be used in the main experimental task. Furthermore, this study provides insights into three different feature dimensions, namely color, size, and orientation. The findings revealed that in this setup, there exists a major variability on the perceptual level (Figure 3), differing largely between the feature dimensions. The overall feature distances of all stimuli used and their variability across participants was smallest in orientation, intermediate for color, and largest for size. Hereby, it is important to acknowledge that the units of measurement were different across features. However, these findings imply that the continuous memory precision across features may not be comparable without standardizing the VWM measure according to the degree individuals are able to perceive differences within a feature.

The statistical findings on the main experiment revealed that Set Size, Feature, and Attention Condition significantly impacted the performance on the VWM task. VWM precision was compromised before the capacity limit of four (Cowan, 2001), but remained substantially better than guessing behaviour. These results clearly argue against the integrated object framework (e.g., Fukuda et al., 2010) but also against the conception of discrete capacities in independent feature models (e.g., Wang et al., 2017). Fukuda et al. (2010) found a neurological marker of memory capacity that reached an asymptote at the set size of four across stimuli differing in their color dimension. The current study revealed contradicting evidence that in the focussed color trials, there was no significant difference between the set size of one and four. It may be that the participants in the current study knew the small pool the colors could stem from, which suggests that VWM resources may be flexible and can go beyond a capacity of four entities according to circumstantial cues. However, it was also observed that orientation was the hardest feature to remember across all trials and in contrast to size and color, memory precision of the set size of four did not become worse in the divided attention trials. Furthermore, the obtained results show that when color had to be remembered in the divided attention, the VWM performance between one and four presented stimuli was suddenly significantly different. The latter effect of the attentional instruction shows that by adding other features to the attention, VWM was compromised of size and especially color, while the hardest feature, orientation, was not compromised in the divided attention. The obtained findings oppose the findings of Wang et al. (2017) that the memory load on one dimension did not affect the memory performance on another dimension. In line with Shin and Ma (2017), the results rather support a VWM model that acknowledges resource pools for features with a certain flexibility to allocate these resources. The compromising effect of memory precision was not observed between the set sizes of one and two in any trial combination, which indicates that the reallocation of resources across features only occurs under “threatening”, demanding circumstances for VWM.

The findings that the memory performance did not differ in either condition between the set size of one and two can also be explained in the light of the “object benefit” described by Schneegans and Bays (2018). It provides an alternative to capacity limit arguments, namely, that in the encoding process of VWM, certain conjunctions of features may have an advantage. In the present VWM task, the two stimuli were presented next to each other and the features were clearly distinguishable from one another due to the liberal pre-experimental results. As participants had answer options to choose from, many reported that comparisons were able to be drawn easily with their mental representation and knowing how the two features were relative to one another. This study’s measurement tool was not able to record a difference even if there was a minor compromise in VWM with the set size of two. Similar implications were found by Balaban and Luria (2016) who emphasized that the sensitive processes in VWM may integrate different stimuli depending on stimulus-driven cues like Gestalt principles, or environmental cues.

Limitations

The experiment was designed with a pre-experimental phase in order to make use of stimuli in the main VWM task that are not categorically different, e.g., with color red and blue, but that are ensured to be discriminable by the individual but close to similar, e.g., different shades of blue. This approach is beneficial in order to account for individual differences in perception and thus, enables the use of an individualized VWM precision measure (ED) on the basis of the personalized answer options. However, during the experiment conduction, it was observed that participants regularly identified the control trials, where equality had to be reported, as different. Therefore, the explanatory power of the obtained results on the basis of this measure may be compromised because the individualized precision measures in this study do not represent perceptual just noticeable differences.

Furthermore, the reported effect of attention may have been confounded because the stimuli of focused attention trials deviated from the divided attention trials. In the focused attention trials, all stimuli shared the same default feature values on the respective non-relevant feature dimensions, whereas stimuli in the divided attention differed from one another on every feature dimension. Regarding the focused attention trials, one can argue that the non-relevant default features were grouped due to their similarity and thus, more resources were able to be allocated to the relevant feature dimension. The performance should have been compared on the basis of the exact same trials despite the attentional instructions in order to reliably infer that attention caused the reported differences in memory precision. However, the answer options provided to the participants in the divided attention displayed the non-relevant feature values of the target (Figure 2B.). Thus, the difference between the focused and divided trials was accounted for in the corresponding answer options, which may have reduced the confounding effect.

Lastly, it is of high importance in behavioural experiments on cognitive performance to ensure identical conditions across all participants. While the response input through mouse clicks in the main experiments' design allowed decreased variability of eye movements compared to keyboard input, other conditions like lighting or screen distance were not able to be standardized and head movements could not be avoided.

Conclusion

In the present study on VWM precision, a unique approach was implemented in order to account for individual differences in perception. The obtained results show that the integrated object model with a discrete capacity of VWM is not a sophisticated explanation for VWM performance. More so, further evidence is provided for flexible feature resources in VWM that tend to be reallocated to the more difficult memory subjects, e.g., the less discriminative object feature at the cost of the more discriminative features. The individual stimuli selection revealed that a behavioural VWM task performance has to be interpreted with the acknowledgment of individual perceptual biases that may influence VWM precision before and during encoding. An extended future framework could be to deliberately compare VWM precision of closely related object features with VWM precision of highly discriminative features, in order to shed light on possible differences in mental representations depending on the circumstances of object similarity. Hereby, the influences of attentional instructions, the number of stimuli, and the consistency across multiple feature dimensions, such as color, size, and orientation, remain of interest.

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