Visual working memory for amplitude-modulated shapes

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We investigated the trade-off between capacity and precision in visual working memory with two different tasks: delayed discrimination and recall. The stimuli were radial frequency patterns that require global pooling of local visual features. The thresholds in delayed amplitude discrimination were measured with a two-interval, forced-choice setup using the Quest procedure. In the recall experiment, the observers' task was to adjust the amplitude of a probe to match the amplitude of a cued item. For one item, the amplitude thresholds were low (0.01–0.05) and the adjustments precise (standard deviations, 0.03–0.05). As the number of items increased from one to six, there was a linear, 6-to-14-fold increase in the thresholds (0.14–0.29) and a 1.5-to-3-fold increase in the standard deviations (0.06–0.11). No sudden or complete breakdown in performance was observed for any subject. The results show a continuous trade-off between memory capacity and precision; six items can be discriminated with the same performance level (75% correct) as one item if the difference between the stimuli is set accordingly. Thus, the stimulus discriminability determines the capacity of visual working memory, and the trade-off between the capacity and precision is linear.

Keywords: visual working memory, shape perception, capacity, precision, radial frequency patterns, psychophysics

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Introduction

Currently it is acknowledged that the precision of representations in visual working memory depends on the number of items concurrently held in the memory (Bays & Husain, 2008; Wilken & Ma, 2004; Zhang & Luck, 2008); we can have a few highly precise representations or multiple representations with lower fidelity. Correspondingly, the memory capacity for complex objects is lower than for simple features due to increased information load (Alvarez & Cavanagh, 2004) or due to limited resolution of the memory slots (Awh, Barton, & Vogel, 2007). While the different views on visual working memory agree, with certain reservations, on the trade-off between the capacity and memory precision, there still is a debate on whether the working memory contains discrete (Awh, Barton, & Vogel, 2007; Anderson, Vogel, & Awh, 2011; Cowan & Rouder, 2009; Rouder et al., 2008; Zhang & Luck, 2008) or continuous resources (Alvarez & Cavanagh, 2004; Bays & Husain, 2008, 2009; Bays, Catalao, & Husain, 2009; Huang, 2010; Wilken & Ma, 2004) for the short-term storage of information. The flexible resources models predict a continuous decrease in the precision of the representations as the number of items increases. The discrete-slots model (Zhang & Luck, 2008; slots + averaging) suggests that memory precision increases with a small number of items because multiple slots can be used to represent the same item, but when the number of items exceeds the number of memory slots, the precision reaches a plateau.

Visual working memory has typically been studied with simple stimuli, such as tilted lines and colored boxes (Bays & Husain, 2008; Luck & Vogel, 1997; Wilken & Ma, 2004; Zhang & Luck, 2008). Instead of these elementary visual features, we used radio frequency (RF) patterns (Wilkinson, Wilson, & Habak, 1998), contour shapes that are processed in the intermediate stages of the visual system (Poirier & Wilson, 2006). Previously we have shown with phase-modulated RF patterns that the capacity of visual working memory is very limited (Salmela, Mäkelä & Saarinen, 2010). In the present study, we measured the memory capacity and memory precision for RF shapes defined by the amplitude and the RF of the pattern. The shapes in the present study range from smooth triangles to spiky star-like patterns (Figure 1), which should be easily discriminated from each other and could be easily preserved in the memory.

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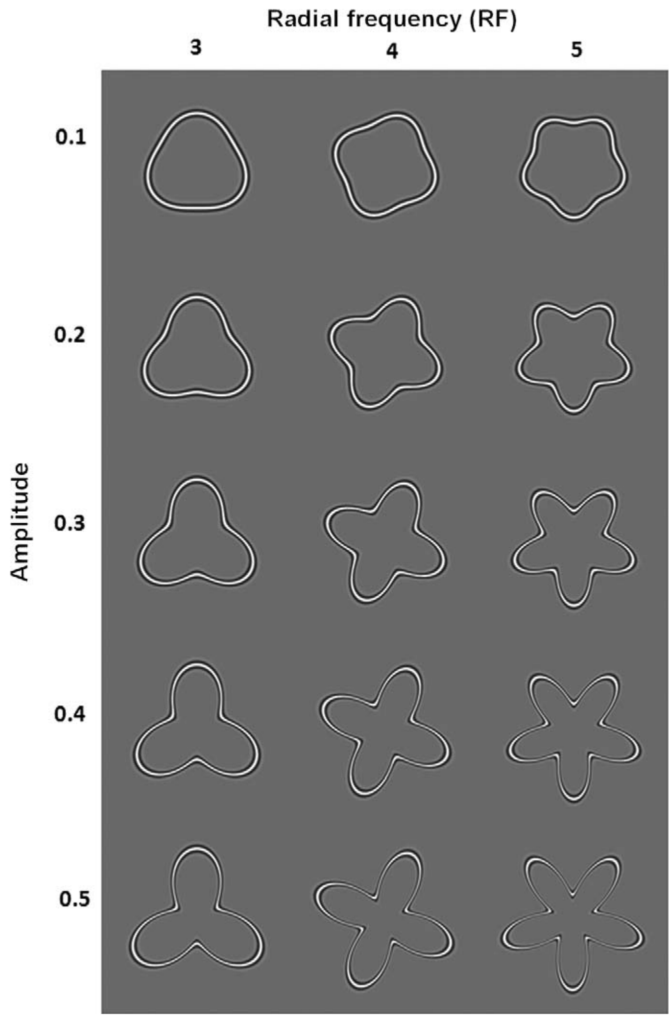

Figure 1. Radial frequency patterns. The radial frequencies 3, 4, and 5 correspond to triangle, square, and star-like shapes, respectively. In addition to RF, the shape can be varied with the amplitude of the modulation.

To investigate the memory capacity and precision for contour shapes, we measured the observers' performance in delayed discrimination and recall tasks. In the two-interval, forced-choice discrimination task, instead of measuring the decline in the observers' performance as the number of items increases, we kept the performance level constant (75% correct) using an adaptive Quest algorithm (Watson & Pelli, 1983), and measured the threshold for delayed discrimination for one to six items. In the recall task, the distribution of memory errors was measured with the method of adjustment for one to six items.

Further, the predictions of the discrete and flexible resources models of visual working memory were tested. The distribution of recall errors reflects the precision of working memory representation, whereas the discrimination threshold is a combination of the probability to remember and the precision of representation (Zhang & Luck, 2008). For a small number of items (one to four), the predictions of the discrete-slots model (Zhang & Luck, 2008) and the dynamic resources (Bays & Husain, 2008) are quite similar to our tasks. Both models predict an increase in discrimination thresholds (Figure 2a) and recall errors (Figure 2b). The flexible resources model suggests an accurate performance for a small number of items and a continuous trade-off between the capacity and precision as the number of items increases. Correspondingly, the slot model suggests that precision can be improved using all the slots when the number of items is less than the number of slots. For multiple items (more than three or four), however, the model predictions differ, and the discrete-slots model predicts points of discontinuity; the thresholds should rise abruptly due to memory failures when the slots are full (Figure 2a), and memory precision should reach a plateau (Figure 2b) when the fixed capacity limit is exceeded.

Methods

Equipment, observers, and stimuli

The stimuli were generated and the experiment conducted with the Matlab (MathWorks Inc., Natcik, MA) and a Mitsubishi Diamond Pro 2070SB display (image area, 11.2 degress $\times$ 8.4 degrees; pixel size, 0.84 arcmin; refresh rate, 100 Hz; mean luminance, 44.5 cd/m^2) controlled by the ViSaGe (Cambridge Research Systems, Cambridge, UK). A chinrest was used to hold the viewing distance constant at 2.0 m. Five observers (two authors) with normal or corrected-to-normal vision participated in both experiments. The experiments were conducted in accordance with the Declaration of Helsinki.

The stimuli were RF patterns, i.e., contour shapes created by sinusoidal modulation of the radius of a circle (Figure 1). Three radial frequencies—3, 4, and 5—were used. The radius of the base circle was 0.6 degrees. The Michelson contrast of the patterns was fixed to 75%. The spatial frequency of the contour was 8 cycles/degree (sigma $=$ 0.056 degrees). The amplitude of the patterns was continuously varied (Figure 1) between 0.1 and 0.5 in proportion to the radius.

Procedure

Two different tasks were used to characterize the memory performance: delayed discrimination and recall. The delayed discrimination thresholds were measured with a two-interval, forced-choice setup. In the first interval, one to six stimulus items were

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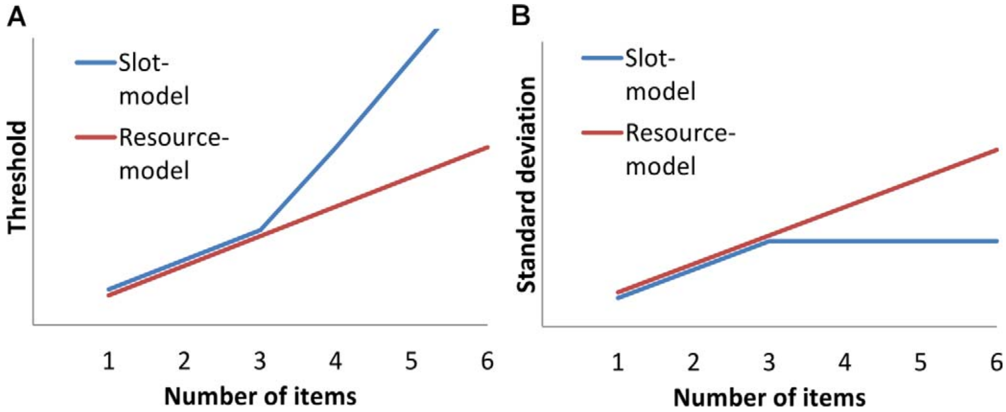

Figure 2. Predictions of the discrete-slots and resource models. (a) Threshold experiment. The resource model suggests a constant increase in the threshold. The discrete-slots model suggests an abrupt rise of the threshold when the fixed capacity limit is exceeded. The increase of the threshold in the Figure is based on a simple three-slot model. When the number of items increases to six, the probability (correct response for 3/n trials and guessing) for correct response in a two-alternative, force-choice task should decrease to 75%, and the threshold should increase rapidly. (b) Adjustment experiment. The resource model suggests a constant increase in the standard deviation of the adjustment errors. The discrete-slots model suggests a constant value when the fixed capacity limit is exceeded.

presented evenly spaced at 2.2 degrees eccentricity from the fixation cross (Figure 3a). After a 1.5-second blank memory period, the second interval with the same number of items in the same locations was presented, but the amplitude of one target item was either increased or decreased (Figure 3a). The observers' task was to indicate whether the changed item had higher amplitude in the first or in the second interval. The amount of amplitude change was varied according to the observers' responses using the Quest algorithm (Watson & Pelli, 1983), and the amplitude threshold for 75% correct discrimination was measured. For the first interval in every trial, the amplitude (0.1–0.5), the RF (3, 4, or 5), and the phase (0–360 degrees) of each RF pattern was randomly selected with one restriction: only two of the items could have the same RF. To avoid the possibility that in some trials the discrimination task could be carried out by finding the target in the second interval with lower/higher amplitude than other stimuli in the display (i.e., pop-out effect), the amplitude of the target was restricted and the changed amplitude was not allowed to be outside the range of 0.1–0.5. The duration of both intervals was 500 ms/item, and hence one item was presented for 500 ms, two items for 1000 ms, and so forth. Each series of threshold measurement consisted of 30 trials. For each number of items, six or seven threshold estimates were measured in total, and the lowest four values were used to calculate the final (average) threshold estimate for each observer.

The distribution of recall errors was measured with a method of adjustment. The experimental setup and stimuli were identical to the discrimination experiment, except that the second interval consisted of a cue box and a probe item (Figure 3b). The observers' task was to adjust the amplitude of the probe to match the amplitude of the item in memory. The observer used two keys to increase and decrease the amplitude of the pattern. When the observer was content with the adjustment, a third key was used to start the next trial. The duration of the adjustment was not restricted. For each array size, 120 trials were performed in blocks of 40 trials.

Analysis of adjustment errors

The adjustment data were modeled using similar types of analysis that had previously been used in recall tasks (Bays, Catalao, & Husain, 2009; Zhang & Luck, 2008). The trials when the stimuli were remembered were modeled with a Gaussian distribution. The trials when the observers made random guesses were modeled with uniform distribution. The sum of these two distributions was fitted, by minimizing the sum of squared residuals, to the distribution of the adjustment errors. The fitting was done with three free parameters: (1) mean of the Gaussian, (2) standard deviation of the Gaussian, and (3) a constant (i.e., uniform distribution). The standard deviation is used as a measure of the precision of the representations, and the constant is used as a measure of random guessing.

In contrast to previous studies in which color stimuli were used (Bays, Catalao, & Husain, 2009; Zhang & Luck, 2008), the response space in the current study was not circular. The observers were unlikely to adjust the stimuli outside the range of amplitude variation (0.1–0.5) and thus the errors will fall to zero at ± 0.4, even if there are no random responses. Further, if the

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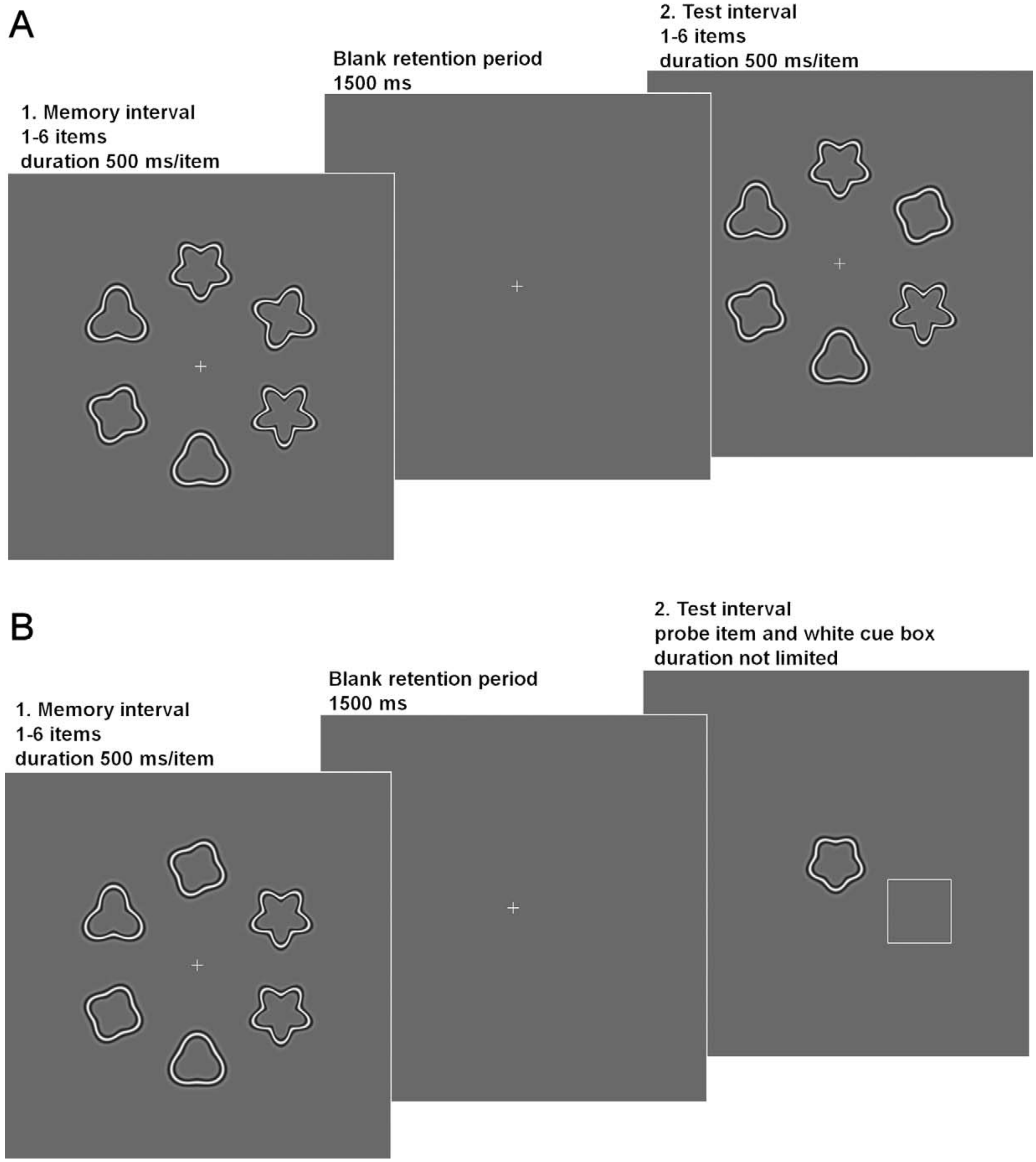

Figure 3. Experiment setups. (a) The delayed 75% amplitude discrimination thresholds were measured using a two-interval, forced-choice setup. In every trial, the amplitude of one randomly selected item increased or decreased, and the observers' task was to say whether the changed item had higher amplitude in the first or second interval. The amount of amplitude change was determined with the Quest procedure. In the example, the changed item is in the top-right position. (b) The recall task was conducted with the method of adjustment. The observers' task was to adjust the probe item presented in the second interval to match the amplitude of the item in memory. In both tasks, the duration of the first interval was 500 ms/item, and thus the stimulus-encoding time increased from 0.5 to 3 seconds as the number of items increased from one to six.

observers, instead of random guessing, always adjusted the shape to average amplitude, the errors will fall to zero at ±0.2, which is the difference between the average and maximum amplitudes. To rule out these possibilities, the data were modeled with a truncated Gaussian error distribution, i.e., the distribution was flat from -0.2 to 0.2 and fell to zero gradually from ±0.2 to ±0.4.

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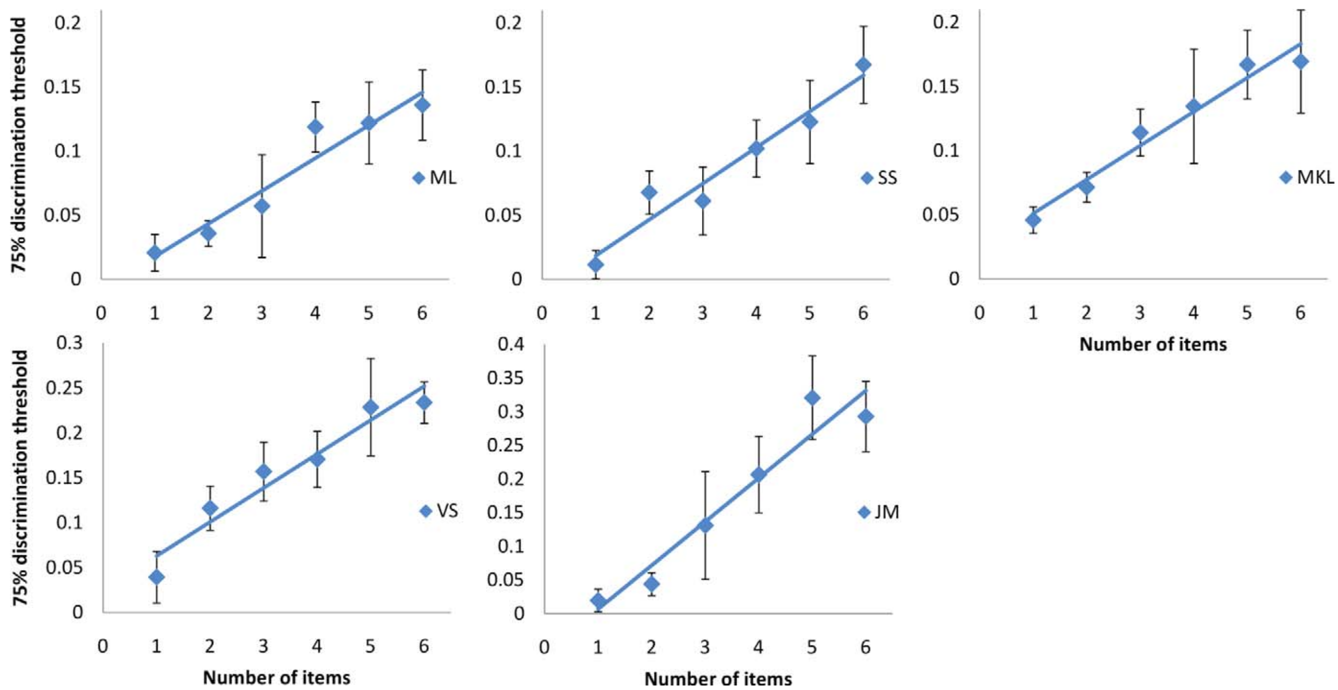

Figure 4. 75% amplitude discrimination thresholds as a function of number of items. Each data point is based on best 4/6-7 Quest series (120 trials). The error bars are 95% confidence intervals, and the lines are linear fits to the data. Note that the *y*-scale varies.

Results

Discrimination thresholds

As expected, the delayed amplitude discrimination threshold for a single item was very low (0.01–0.05) for every observer (Figure 4). As the number of items increased from one to six, the discrimination thresholds increased steeply ($F[1, 5] = 9.011$, $p < 0.001$), and for six items, the thresholds were 6-to-14-fold (0.14–0.29) compared to single-item thresholds ($t[8] = -5.967$, $p < 0.001$). There were some differences between the observers (Figure 4), but for every observer, the linear fits were very good (average $R^2 = 94\%$ [93–96%]). The slopes of the fitted lines were identical for observers ML (0.025), MKL (0.026), and SS (0.028), but slightly higher for observers VS (0.038) and JM (0.065).

The RF and the amplitude of the stimuli were randomly set for every trial. However, the RF or the amplitude (especially the highest and lowest values) of the pattern could affect the discriminability of the stimulus, i.e., it could be easier to discriminate the amplitude change in RF3 than in RF4. To rule out this possibility, the effect of the RF and the amplitude of the pattern on correct responses in the discrimination task were further tested with the analysis of variance. All the trials were combined and correct responses for the different RFs (3, 4, and 5) and amplitude ranges (0.10–0.19, 0.20–0.29, 0.30–0.39, and 0.40–0.50) were calculated. The RF ($F[2, 14] = 0.453$, $p = 0.646$) and the amplitude ($F[3, 19] = 0.578$, $p = 0.638$) did not have a significant effect on the number of correct responses.

Adjustments

The distribution of adjustment errors followed a Gaussian distribution (Figure 5), and the fits of the sums of Gaussian and uniform distributions were good (average $R^2 = 95\%$ [87–99%]). Further, the observers did not make any random adjustments (i.e., the tails of the distributions are close to zero), and the constant parameter (= uniform distribution) was virtually zero (< 0.001). With a single item (Figure 5), the adjustments were very precise (standard deviation of the fitted Gaussian, 0.03–0.05). As the number of items increased from one to six, the standard deviation of the adjustment errors increased slightly ($F[1, 5] = 4.815$, $p < 0.05$), and for six items, the standard deviations were 1.5-to-3-fold (0.06–0.11; $t[8] = -3.991$, $p < 0.01$) compared with a single item condition (Figures 5 and 6). There was some variation in the mean of the fitted Gaussian (Figure 5), and on average it differed from zero ($t[29] = 4.418$, $p < 0.01$). However, the bias was not systematic and did not depend on the number of items ($F[1, 5] = 0.916$, $p = 0.488$).

The increase of the standard deviation of the adjustment errors and a lack of random responses was confirmed with additional analysis. Instead of uniform distribution, truncated Gaussian distribution was used to model the random errors. The standard

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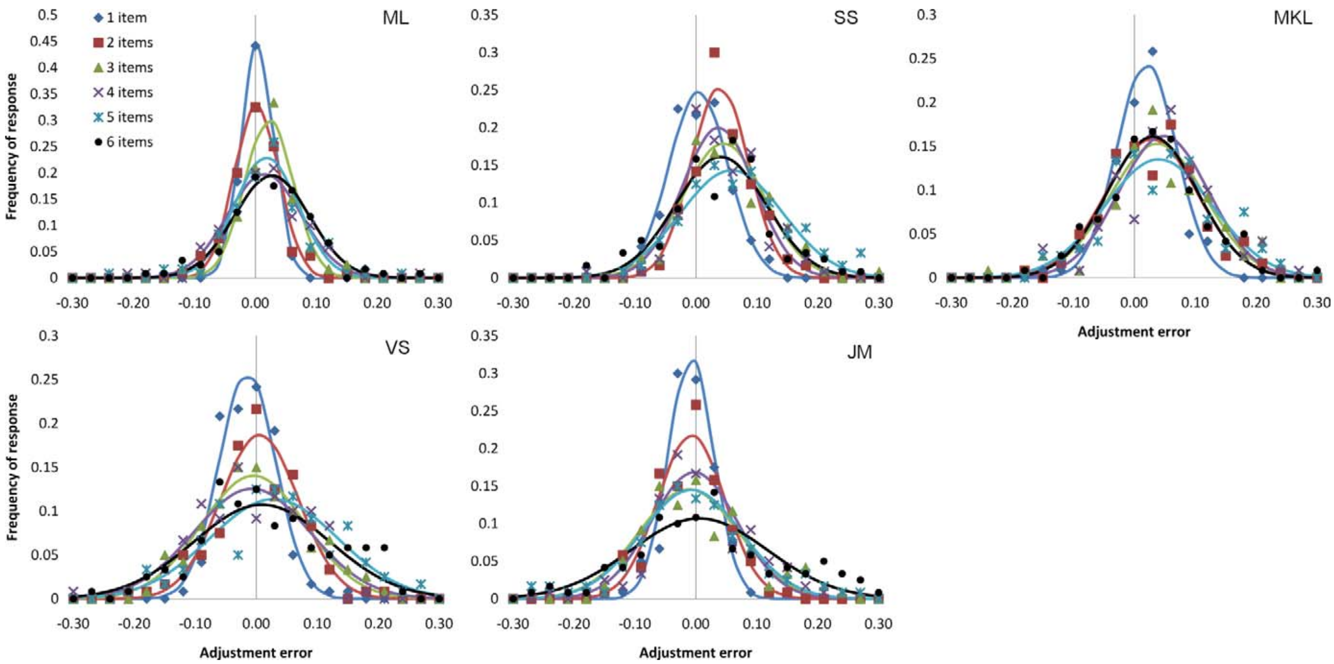

Figure 5. Distribution of recall errors. Sums of Gaussian and uniform distributions were fitted to the data with three free parameters (mean, standard deviation, constant).

deviation of the errors was identical to the original analysis, and the truncated error distribution did not reveal any random adjustments either.

The increase in the standard deviation of the adjustment errors was quite linear. The linear fits (Figure 6) were moderate, average $R^2 = 77\%$ (43–96%). When one outlier (MKL) was removed, the fits were good, average $R^2 = 84\%$ (73–96%). The slopes of the lines (Figure 6) were gradual for observers MKL (0.005), ML (0.007), and SS (0.007), and a bit steeper for observers JM (0.013) and VS (0.014).

With the analysis of variance, the effect of the amplitude (0.10–0.19, 0.20–0.29, 0.30–0.39, and 0.40–0.50) on the absolute adjustment error was tested. The

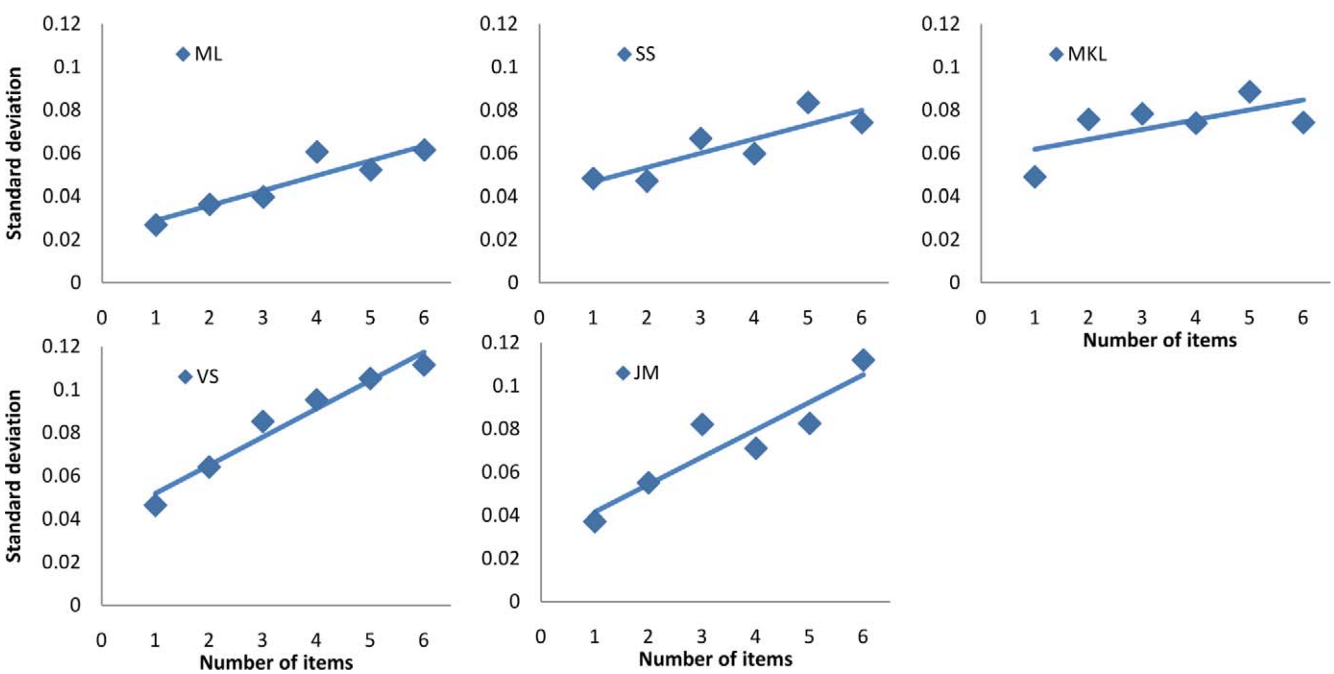

Figure 6. The standard deviations of the adjustment errors. The standard deviation was calculated from the Gaussian functions fitted to the error distributions. Each data point is based on 120 trials. The lines are linear fits to the data.

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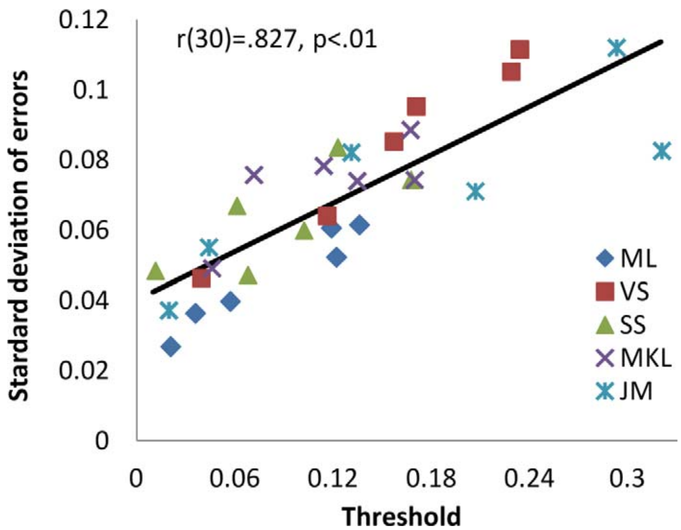

Figure 7. Correlation analysis. The correlation between the discrimination threshold and the standard deviation of adjustment errors.

amplitude ($F[3, 19] = 2.962$, $p = 0.064$) did not have a significant effect on the errors.

Comparison of the tasks

Both the thresholds and standard deviation of the adjustment errors increased linearly. To confirm the similarity between the measures, a correlation analysis was conducted. Pearson correlation between thresholds and adjustments was high ($r[30] = 0.827$, $p < 0.01$) (Figure 7; individual correlations varied from 0.74 to 0.98). The correlation between the tasks also remained significant after controlling for the number of items, partial correlation ($r[27] = 0.635$, $p < 0.01$). Thus, both the task performance as such (partial correlation) and the performance combined with the decrease in performance correlated significantly.

Discussion

We tested (1) whether the memory capacity for amplitude-modulated shapes is similarly limited as for phase-modulated shapes (Salmela, Mäkelä, & Saarinen, 2010); (2) if working memory resources are discrete or continuous; and (3) if the trade-off between memory capacity and precision is similar in delayed discrimination and recall. The results show a larger capacity for amplitude-modulated RF patterns than for phase-modulated patterns (Salmela, Mäkelä, & Saarinen, 2010). The linear increase in both the discrimination thresholds and the standard deviation of the recall errors suggest that the visual working memory resources are continuous. Furthermore, the results show that the trade-off between memory capacity and precision is similar in the forced-choice discrimination and in subjective-recall tasks. Thus, the stimulus discriminability, not the discrete slots, determines the capacity and the fidelity of the representations in visual working memory, and the trade-off between capacity and precision is linear.

In our previous working memory study, we used two-component RF patterns and measured the accuracy of change detection (Salmela, Mäkelä, & Saarinen, 2010). The capacity of visual working memory for contour shapes was severely limited, and the observers were able to detect the change in shape accurately only in one item. The contours were constructed from two RF components, and the shape was determined by the phase difference between the components. An accurate detection ($d' > 2$) of the change with one item required quite a large relative phase difference (10%–17%), and the observers' performance collapsed already with two items. Because the task in the present study required a lower performance level (a 75% threshold) and humans are highly accurate in detecting amplitude deviations of RF patterns (Wilkinson, Wilson, & Habak, 1998), better performance for amplitude-modulated shapes in the memory tasks was expected. The linear increase in the discrimination thresholds up to six items and the lack of recall errors were, however, quite surprising.

The forced-choice discrimination task could only be performed correctly if most of the items were stored in memory. The ability to remember six items was not due to the pop-out effect or the target being different from the distractor items, but instead suggests that memory resources can be distributed to six items. However, the cost is reduced sensitivity to amplitude changes and an increase in the discrimination threshold to 6-to-14-fold with six items. In comparison, the standard deviations of the adjustment errors increased only slightly (a 1.5-to-3-fold increase) for six items and were surprisingly low. This could suggest that the trade-off is stronger in discrimination than in recall, but more likely the explanation for the different slope is the differences in the setup. Furthermore, the correlation between the thresholds and standard deviation of adjustment errors was high. This suggests that both tasks measure the same memory process.

The capacity of visual working memory has usually been estimated based on the decrease in the observers' performance in discriminating or detecting a constant difference in the stimuli. We measured the amount of difference between the two sets of stimuli required for 75% correct discrimination. Our results show that the observers are able to discriminate one to six items with the same level of accuracy as long as the difference between the stimuli to be discriminated is set accord-

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ingly. We measured up to six memory items and observed no sudden or complete breakdown in performance or capacity limitation. This suggests that with appropriate stimuli—when the scale of stimulus changes is large enough—even a larger number of items could be remembered.

The clear distinction between the two main views on the limited memory resources is that the slot-based models (e.g., Zhang & Luck, 2008) predict a point of discontinuities when the memory slots are full, whereas the flexible resources models (e.g., Bays & Husain, 2008) predict constant changes in the observers' performance. We measured the working memory performance with two tasks (a total of 1,440 trials for each observer), and none of our observers showed any discontinuities in memory performance. The variability of memory performance between the observers is quite low, especially in the two-interval, forced-choice discrimination task. The linear decrease in the performance and the absence of discontinuities suggest no need to postulate complex mechanisms (e.g., slots or averaging) for memory. Further, the lack of random adjustments is not compatible with slot-based models on working memory.

The steady linear increase of the observers' discrimination threshold is quite different from the previously reported sudden drop between three and six items in probability to remember the presented items (Zhang & Luck, 2008). The sudden drop has been reported for both color stimuli and Fourier descriptors (Zhang & Luck, 2008) that quite closely resemble our radial frequency shapes, and hence the difference between the stimuli is not a likely explanation for the discrepant results. A more likely explanation is the differences between the experimental methods and analyses, e.g., the decrease of the P(m) parameter (probability to remember) from one to six items in the results of Zhang & Luck (2008) is quite close to linear (their figure 2a and supplementary Figure 5a). However, they do not report results from four and five items, and thus it remains inconclusive whether the drop is sudden, as they suggest, or linear, as our results suggest.

The different memory capacity for amplitude- and phase-modulated (Salmela, Mäkelä, & Saarinen, 2010) shapes likely reflects the different sensitivities of the visual system to radial phase and amplitude. This suggests that the performance in the visual memory task is primarily limited by the discriminability of the stimulus. Without a delay, the visual system is, however, highly accurate in detecting and discriminating shapes, and hence the representations as such must be very precise. When the retention time or the number of items to be remembered increases, the noise inherent in the neural systems accumulates and deteriorates the representations (Wilken & Ma, 2004; Najima, Dosher, Chu, & Lu, 2011). The noise as such, however, cannot explain the difference between amplitude- and phase-modulated shapes.

A recent fMRI experiment suggests that the same mechanisms or cortical areas are used for both visual encoding and short-term maintenance of the visual information (Harrison & Tong, 2009). If the same neural mechanisms both encode and maintain the visual representations, the memory precision for multiple items is surprisingly poor given the highly efficient and accurate visual system. What limits the precision of multiple items, and why are amplitude- and phase-modulated shapes remembered quite differently? A good performance in the visual task is expected when the stimuli are processed in different neural mechanisms. If the multiple stimuli are processed within the same mechanism, masking limits the performance. There is some evidence for shape channels sensitive to different radial frequencies in the visual system (Bell & Badcock, 2009; Bell, Wilkinson, Wilson, Loffler, & Badcock, 2009), and within-channel masking could explain the difference between our previous (Salmela, Mäkelä, & Saarinen, 2010) and current results. Remembering multiple, phase-modulated, shapes composed of the same RFs might be more difficult than remembering multiple shapes composed of different RFs because the shapes composed of same RFs are processed within the same neural mechanisms and exposed to stronger masking or mutual interference. Within-channel masking could also explain some of the category effects in visual working memory, e.g., the better memory performance between categories than within category (Olsson & Poom, 2005).

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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, 15*, 106–111.

Anderson, D. E., Vogel, E. K., & Awh, E. (2011). Precision in visual working memory reaches a

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stable plateau when individual item limits are exceeded. *The Journal of Neuroscience, 31*, 1128–1138.

Awh, E., Barton, B., & Vogel, E. K. (2007). Visual working memory represents a fixed number of items regardless of complexity. *Psychological Science, 18*, 622–628.

Bays, P. M., & Husain, M. (2008). Dynamic shifts of limited working memory resources in human vision. *Science, 321*, 851–854.

Bays, P. M., & Husain, M. (2009). Response to comment on "Dynamic shifts of limited working memory resources in human vision." *Science, 323*, 877d.

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, 1–11, http://www.journalofvision.org/content/9/10/7, doi:10.1167/9.10.7.

Bell, J., & Badcock, D. R. (2009). Narrow-band radial frequency shape channels revealed by sub-threshold summation. *Vision Research, 49*, 843–850.

Bell, J., Wilkinson, F., Wilson, H. R., Loffler, G., & Badcock, D. R. (2009). Radial frequency adaptation reveals interacting contour shape channels. *Vision Research, 49*, 2306–2317.

Cowan, N., & Rouder, J. N. (2009). Comment on "dynamic shifts of limited working memory resources in human vision." *Science, 323*, 877.

Harrison, S. A., & Tong, F. (2009). Decoding reveals the contents of visual working memory in early visual areas. *Nature, 458*, 632–635.

Huang, L. (2010). Visual working memory is better characterized as a distributed resource rather than discrete slots. *Journal of Vision, 10*(14):8, http://www.journalofvision.org/content/10/14/8, doi:10.1167/10.14.8.

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature, 390*, 279–281.

Najima, R., Dosher, B., Chu, W., & Lu, Z.-L. (2011). Visual working memory performance with contrast and external noise: A load-dependent perceptual template model account. *Journal of Vision, 11*(11): 1254, http://www.journalofvision.org/content/11/11/1254, doi:10.1167/11.11.1254.

Olsson, H., & Poom, L. (2005). Visual memory needs categories. *Proceedings of the National Academy of Sciences, 102*, 8776–8780.

Poirier, F. J., & Wilson, H. R. (2006). A biologically plausible model of human radial frequency perception. *Vision Research, 46*, 2443–2455.

Rouder, J. N., Morey, R. D., Cowan, N., Zwilling, C. E., Morey, C. C., & Pratte, M. S. (2008). An assessment of fixed-capacity models of visual working memory. *Proceedings of the National Academy of Sciences USA, 105*, 5975–5979.

Salmela, V. R., Mäkelä, T., & Saarinen, J. (2010). Human working memory for shapes of radial frequency patterns. *Vision Research, 50*, 623–629.

Watson, A. B., & Pelli, D. G. (1983). QUEST: A Bayesian adaptive psychometric method. *Perception & Psychophysics, 33*, 113–120.

Wilken, P., & Ma, W. J. (2004). A detection theory account of change detection. *Journal of Vision, 4*(12):11, 1120–1135, http://journalofvision.org/4/12/11/, doi:10.1167/4.12.11.

Wilkinson, F., Wilson, H. R., & Habak, C. (1998). Detection and recognition of radial frequency patterns. *Vision Research, 38*, 3555–3568.

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature, 453*, 233–235.

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