The impact of item clustering on visual search: It all depends on the nature of the visual search

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Decades of vision research on how people search for a target item among distractor items have always avoided item clustering. Instead, researchers made sure that items were evenly distributed in search displays. This, however, is rarely the case in our everyday visual environment. Consequently, it is largely unknown how item clustering may impact visual search performance. In this study, I manipulated item clustering in search displays. In an easy feature search, observers looked for a target letter "T" among distractor letters "Os" and reported whether the target was pointing to the left or to the right. In a difficult spatial configuration search, observers searched and reported the orientation of the target letter "T" among distractor letters "Ls". The two types of searches thus had the same target but different distractors. In two experiments, I found that while item clustering slowed down the easy feature search, it speeded up the difficult spatial configuration search. Together, these results show that item clustering significantly affects visual search performance and its exact impact (negative or positive) depends on the nature of the visual search.

Keywords: attention, perceptual organization, search, visual cognition

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Introduction

Items in our environment are rarely uniformly distributed, but rather they often cluster together, such as the apples on a tree, objects in a living room, or people in the mall. Yet, decades of vision research on how people search for a target item among distractor items have avoided item clustering. Instead, researchers made sure that items were evenly distributed in search displays (e.g., Treisman & Gormican, 1988; Treisman & Gelade, 1980; Wolfe, 1994). As a result, how item clustering may impact visual search performance is largely unknown. If the goal of laboratory studies of visual search is to ultimately help us understand how visual search operates in the real world, then we will need to take into account item clustering and examine its impact on visual search.

Researchers initially argued that there are two types of visual searches, dictated by whether a parallel preattentive or a serial attentive mechanism is engaged (e.g., Treisman, 1988; Wolfe, 1994). While search is fast and accurate under the parallel preattentive processing, it is slow and error prone under the serial attentive processing. Over the years, researchers have noted that the distinction between these two types of searches is somewhat blurry, and that search performance can reflect the interplay of a number of cognitive mechanisms (e.g., Duncan & Humphreys, 1989; Wolfe, 1998; see also Treisman, 1988; Wolfe, 1994). Some have argued that visual search may be better understood from a visual object processing prospective (e.g., Enns & Rensink, 1990; Nakayama & Joseph, 1998).

Because item clustering allows the formation of structures and hierarchies in an otherwise homogenous visual scene, how would the presence of item clustering impact visual search performance (see the examples shown in Figure 1)? Would it be the same for different types of visual searches, or would it depend on the nature of the search? Although the impact of clustering on visual search has not been directly studied before, two lines of previous research on visual object perception and attention may be relevant here.

Researchers have found that when an object contain parts or complex internal structures, while our visual system parses such an object into its constituent parts (e.g., Arguin & Saumier, 2004; Xu & Singh, 2002), access to these constituent parts may not be parallel across different objects. The visual system is obligated to access the entire object before it can access parts of that object (see Hochstein & Ahissar, 2002). This may cause parts from the same object to be represented more closely together than parts from different objects, resulting in more conjunction errors from features belonging to the same than different perceptual units (Prinzmetal, 1981; Prinzmetal & Millis-Wright, 1984; see also Treisman, 1982). This may also render low-level features of an object (such as the curvature of the mouth of a face) to be harder to access when high-level representation is formed for the entire object (Suzuki & Cavanagh, 1995). If we treat a cluster of items (see Figure 1) as a complex visual perceptual unit with internal structures, these prior studies would predict that the presence of item clusters in a visual display may hinder direct and fast access to each item in the cluster and slow down visual search performance.

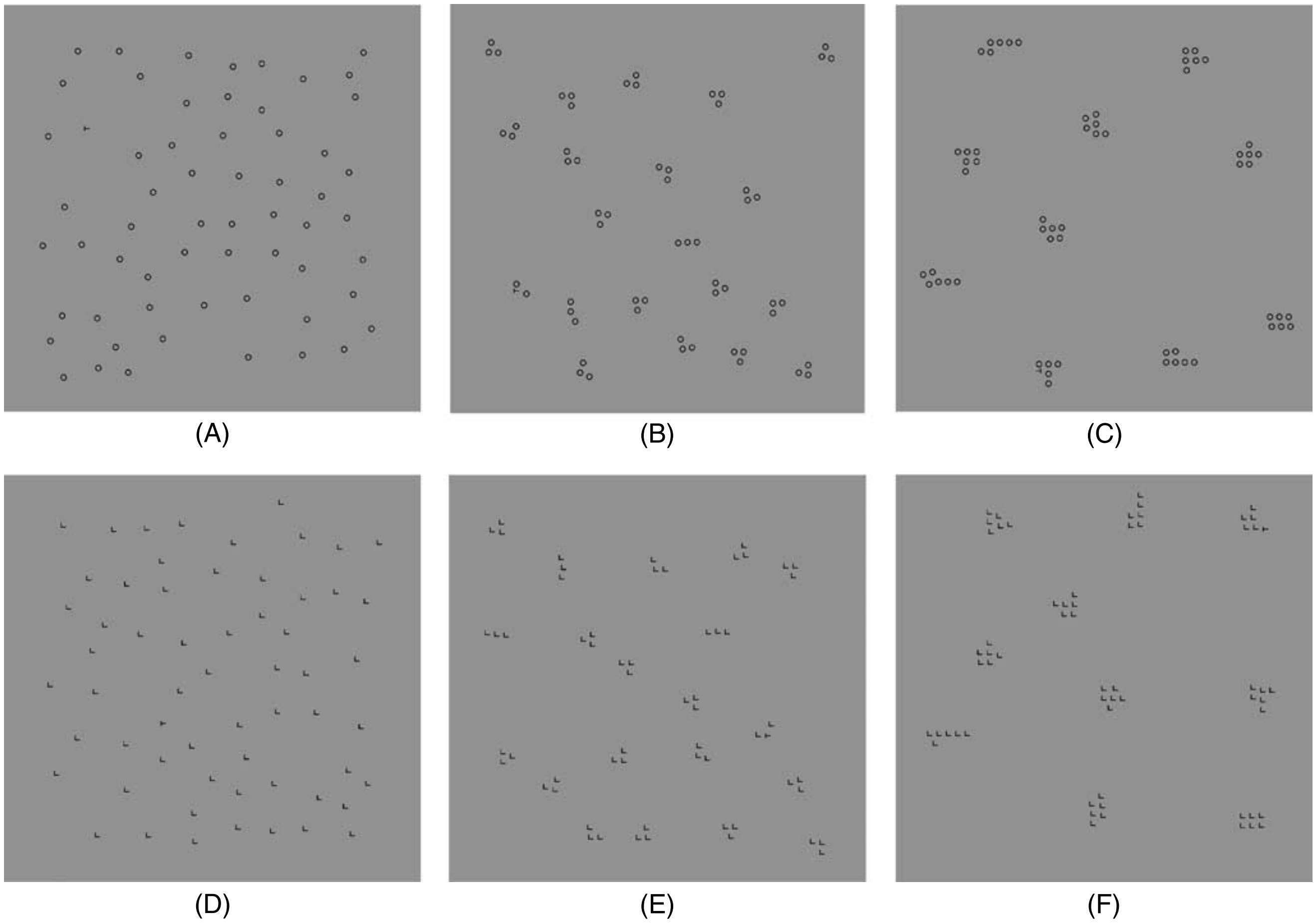

Figure 1. Sample displays from Experiment 1. (A–C) Simple feature search displays in which observers searched for the target letter "T" among distractor letters "Os" and judged whether the target letter "T" was pointing to the right or to the left. (D, E) Spatial configuration search displays in which observers searched for the target letter "T" among distractor letters "Ls" and judged its orientation. The size of the individual clusters varied continuously from 1 to 6 in different display conditions. Display examples for cluster size 1 (A and D), cluster size 3 (B and E), and cluster size 6 (C and F) are shown here. Across the different display conditions, the number of items in a display was always fixed (60 total), as were the size of the overall spatial envelope and the between-item distance within a cluster.

In another line of research, researchers studied how we attend to information either at the local or at the global level (e.g., either attend to the small letters in the display—local processing, or the big letter created by the spatial arrangement of the ensemble of small letters—global processing, see Navon, 1977). It was found that while global level of processing influences local level of processing, the reverse was minimal, suggesting that global processing precedes local processing in visual scene/object analysis (the "global precedence" effect; Navon, 1977; see Kimchi, 1992, for a review of this literature). These results suggest that when faced with clustered visual displays, our visual system may be automatically drawn to the global aspects of the displays (i.e., the clusters) and this may hinder direct access to the individual items in each cluster and slow down visual search performance.

Item clustering necessarily increases item density in a local area, which may negatively impact feature extraction and slow down search. A study by Treisman (1982) found that dense displays were actually searched faster than sparse displays for both feature and conjunction searches. However, Treisman did not control for eccentricity and dense items were closer to fovea on average than sparse items. After controlling for eccentricity and item number, Cohen and Ivry (1991) found that while feature search was not affected by density manipulation, conjunction search slowed down for high-density displays. If item clustering only affects item density, then these previous findings would predict that item clustering would have no effect on a feature search but would slow down a conjunction search.

On the other hand, clustering does provide structure and order to an otherwise homogenous visual display. This may allow an observer to better allocate attentional resources and more efficiently search through the display, resulting in faster search performance.

To understand how item clustering may impact visual search, in this study, I manipulated item clustering in search displays (see Figure 1). In an easy search (a feature search), observers searched for a target letter "T" among distractor letters "Os" and reported whether the target was pointing to the left or to the right. In a difficult search (a spatial configuration search), observers searched and reported the orientation of the target letter "T" among distractor letters "Ls". The two types of searches thus had the same target but different distractors. Because it was not possible to control for all the parameters simultaneously, in Experiment 1, while varying the number of items in a cluster, I controlled for the total number of items in a display, the item-to-item distance within a cluster, and the overall spatial extent of the display across the different conditions; and in Experiment 2, instead of keeping constant the total number of items in a display, I kept the total number of clusters constant and varied the number of items in a cluster continuously across the different display conditions.

To anticipate, results from the two experiments showed that while item clustering slowed down the easy feature search, it speeded up the difficult spatial configuration search. Thus, item clustering significantly impacts visual search performance, and the direction of this impact (negative or positive) depends on the nature of the visual search.

Experiment 1

In this experiment, each trial contained 60 items located in a fixed spatial envelope (see Figure 1 for some examples). These items formed either 60 clusters with 1 item per cluster, 30 clusters with 2 items per cluster, 20 clusters with 3 items per cluster, 15 clusters with 4 items per cluster, 12 clusters with 5 items per cluster, or 10 clusters with 6 items per cluster. The item-to-item distance within a cluster was held constant across the different displays. Thus, with the total item number, the spatial envelope, and the within cluster item-to-item distance held constant, the size of the individual clusters (cluster size) varied continuously from 1 to 6 in different search displays.

Methods

Participants

Fourteen participants (10 females, 4 males; mean age of 21.00 years with *SD* of 1.75 years) with normal color vision participated in Experiment 1. Participants were students of Harvard University and received course credit for their participation. Three additional participants were tested but excluded due to either computer program failure (one participant) or participants' error rate being greater than 10% (two participants) despite repeated instructions emphasizing response accuracy (see below).

Materials and design

There were six display conditions in the experiment. Within each of these display conditions, the number of items remained constant (60 items), but the number of clusters varied continuously from 1 to 6. The items were either distributed in 60 clusters of 1 item per cluster, 30 clusters of 2 items per cluster, 20 clusters of 3 items per cluster, 15 clusters of 4 items per cluster, 12 clusters of 5 items per cluster, or 10 clusters of 6 items per cluster. The clusters were evenly distributed in the display. In the easy search (a feature search), observers searched for a target letter "T" among distractor letters "Os" and reported whether the target was pointing to the left or to the right. In the difficult search (a spatial configuration search), observers searched and reported the orientation of the target letter "T" among distractor letters "Ls" (always upright). The two types of searches thus had the same target but different distractors. Examples of the displays used are shown in Figure 1.

Trials from the two types of searches were blocked. A given block of trials contained 62 trials, including 2 practice trials at the beginning and 10 experimental trials from each of the 6 display conditions randomly intermixed. Participants completed five blocks of trials for one search type before they did so for the other search type, with the testing order counterbalanced across the different participants. All the letters used were black against a light gray background. Each letter subtended $0.5° \times 0.5°$. The entire search display subtended $31.8° \times 31.8°$, and the distance between items within a cluster was about $0.8° \times 0.8°$.

Search response accuracy was repeatedly emphasized over response speed. Participants were asked to be as accurate as they could and then be as fast as they could. This allowed response accuracy to reach ceiling and, consequently, any impact of item clustering on search performance would only appear in response speed.

Apparatus

Stimulus generation and response recording were done using Matlab Psychophysics toolbox (Brainard, 1997) on an Apple iMac computer running a 2.8-GHz Intel Core Duo processor and equipped with a 24-inch LCD monitor.

Procedure

Participants were seated in a dimly lit, quiet room, about 50 cm away from the computer screen. The instructions for the experiment were displayed on the computer screen. Participants completed a practice session consisting of 18 trials before they proceeded with each of the two experimental sessions (one for the feature search and one for the spatial configuration search).

Participants pressed the space key to start either the practice or the experimental session. Each trial consisted

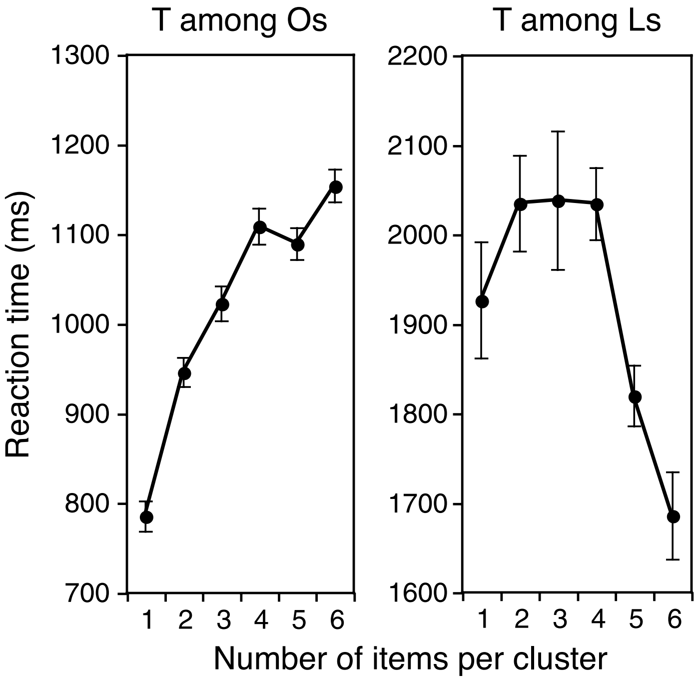

Figure 2. Reaction time data from Experiment 1. For the easy feature search, search time increased with increasing cluster size and plateaued at about cluster size 4. For the difficult spatial configuration search, however, search time did not vary with cluster size up to 4 and then decreased with further increase in cluster size. Thus, while increasing item clustering slowed down the simple feature search, it facilitated the more difficult spatial configuration search. Error bars indicate within-subject standard errors.

of a blank interval of 1,000 ms, followed by a fixation dot (black circle with a diameter subtended 0.3°) at the center of the screen for 500 ms. The search display was then presented. Participants had 8,000 ms to find the target "T" and report its orientation by pressing either the left or the right arrow key on the keyboard with their right index finger. Response accuracy and reaction time were recorded. The search display remained on the screen until a response was made or the 8,000-ms response window ended. Participants were given instant feedback on their performance—they would hear a "beep" if an error was made or if no response was registered within the 8,000-ms response window. Trials came one after another within a block. There were breaks between the blocks during which participants could rest for as long as they needed. The experiment lasted for about 45 min.

Results

Response accuracy and reaction time (RT) for correct trials were analyzed, with RTs analyzed without any truncation (RT results are plotted in Figure 2). Overall, there was a significant effect of search type in both response accuracy and RT ($F(1,11) = 9.37$, $p = 0.01$, and $F(1,11) = 624.87$, $p < 0.001$, respectively), indicating that a spatial configuration search was more difficult than a simple feature search, consistent with findings from previous studies (e.g., Treisman, 1988; Wolfe, 1994). There was also a significant interaction in RT (but not in accuracy) between search type and the number of clusters present ($F(5,55) = 16.52$, $p < 0.001$), showing that the impact of item clustering was different for the two types of searches. Detailed analyses within each of the two search types were performed below.

Feature search for T among Os

Accuracy. The averaged response accuracy was 97.7% and did not differ among the different cluster size conditions ($F < 1$). The percent accuracies for cluster sizes 1 to 6 and SE were: 97.1 (0.5), 97.4 (0.9), 97.5 (0.8), 97.2 (0.8), 98.3 (0.6), and 98.7 (0.7), respectively.

RT. Overall, the effect of cluster size was significant ($F(5,55) = 46.027$, $p < 0.001$). Among cluster sizes 1 to 4 displays, the overall cluster size effect was significant ($F(3,33) = 47.24$, $p < 0.001$). Specifically, in pairwise comparisons, the differences were: Between sizes 1 and 2, $F(1,11) = 33.70$, $p < 0.001$; between sizes 2 and 3, $F(1,11) = 7.51$, $p < 0.05$; and between sizes 3 and 4, $F(1,11) = 7.08$, $p < 0.05$. Among sizes 4 to 6 displays, the overall cluster size effect, however, was not significant ($F(2,22) = 2.62$, $p = 0.096$). Specifically, in pairwise comparisons, the differences were: Between sizes 4 and 5, $F < 1$; between sizes 4 and 6, $F(1,11) = 2.66$, $p = 0.13$; and between sizes 5 and 6, $F(1,11) = 5.31$, $p < 0.05$. These results show that RT increased with increasing cluster size and reached a plateau at about size 4. In other words, item clustering generally slowed down search performance with increasing cluster size.

Spatial configuration search for T among upright Ls

Accuracy. The averaged response accuracy was 96.1% and did not differ among the different cluster size conditions ($F(5,55) = 1.25$, $p > 0.30$). The percent accuracies for cluster sizes 1 to 6 and SE were: 96.7 (0.7), 95.6 (1.1), 95.0 (1.0), 97.0 (0.5), 96.4 (0.7), and 96.2 (0.7), respectively.

RT. Overall, the effect of cluster size was significant ($F(5,55) = 5.77$, $p < 0.001$). Among sizes 1 to 4 displays, however, the overall cluster size effect was not significant ($F < 1$). Specifically, in pairwise comparisons, the differences were: Between sizes 1 and 2, $F(1,11) = 1.23$, $p > 0.29$; between sizes 2 and 3, $F < 1$; and between sizes 3 and 4, $F < 1$. Among sizes 4 to 6 displays, the overall cluster size effect was significant ($F(2,22) = 19.63$, $p < 0.001$).

Specifically, in pairwise comparisons, the differences were: Between sizes 4 and 5, $F(1,11) = 17.32$, $p < 0.01$; and between sizes 5 and 6, $F(1,11) = 9.10$, $p < 0.05$. These results show that RT did not vary with the increase in cluster size from 1 to 4 but then decreased with further decrease in cluster size. In other words, item clustering facilitated search performance at higher cluster sizes.

Discussion

Results from Experiment 1 showed that, for the easy feature search, search time increased with increasing cluster size and plateaued at about cluster size 4. For the difficult spatial configuration search, however, search time did not vary with cluster size up to 4 and then decreased with further increase in cluster size. Thus, while increasing item clustering slowed down the simple feature search, it speeded up the more difficult spatial configuration search.

Although it is tempting to conclude that cluster size 4 may be special, a number of other factors may play a role here. While varying the number of items in a cluster, Experiment 1 controlled for the total number of items in a display, the item-to-item distance within a cluster, and the overall spatial extent of the display across the different display conditions. However, it was not possible to simultaneously control for the total number of clusters, the center-to-center distance between clusters, and the edge-to-edge distance between clusters. The interplay between the latter factors may determine exactly when RT plateaus or decreases with an increase in cluster size during search. Although further detailed investigation is needed to fully understand how item clustering affect visual search, what is clear from the present results is that item clustering significantly impact visual search.

In this experiment, while keeping the total number of items fixed, what would happen if we further decrease the number of clusters by increasing the cluster size until we have one big cluster containing all the items? We would again have a homogenous display but with a smaller item spacing than the display we start out with. At this point, based on the current results, search would likely speed up again for the feature search and slow down for the spatial configuration search, resulting in an inverted U-shaped function for feature search and an upright U-shaped function for spatial configuration search if we plot results according to the number of clusters present in the display (i.e., from 60 to 1). Further studies are needed to verify this performance outcome. Note that when there are N evenly distributed items, the display can either be viewed as containing one large cluster with N items in it, or N clusters each having one item. Given this subjectivity, a U- or an inverted U-shaped function may not be meaningful. The best way to characterize a display would be to describe whether items are evenly distributed or form multiple clusters. With that manipulation, this experiment shows that item clustering significantly impacts visual search performance.

Experiment 2

To verify the effect of item clustering on visual search, in this experiment, instead of keeping constant the total number of items in a display, the total number of clusters was held constant to 10, but the number of items in a cluster varied continuously from 1 to 5 across the different display conditions. This resulted in the total number of items in the search display to vary continuously from 10 to 50. For each clustered display, there was also a control display (the non-clustered display) that contained the same number of total items but evenly distributed. In the spatial configuration search, the distractor letter "L" was rotated, instead of always being upright as was in Experiment 1. As in Experiment 1, the item-to-item distance within a cluster as well as the overall spatial extent of the display across the different conditions were held constant.

Methods

Participants

Sixteen new participants (12 females, 4 males; mean age of 20.56 years with *SD* of 2.42 years) from the same subject pool participated in Experiment 2.

Materials, design, and procedure

There were a total of nine conditions in this experiment: (1) Ten evenly distributed items, (2a) twenty items forming ten clusters with two items per cluster, (2b) twenty evenly distributed items, (3a) thirty items forming ten clusters with three items per cluster, (3b) thirty evenly distributed items, (4a) forty items forming ten clusters with four items per cluster, (4b) forty evenly distributed items, (5a) fifty items forming ten clusters with five items per cluster, and (5b) fifty evenly distributed items. As in Experiment 1, participants were asked to find the target letter "T" and report its orientation with accuracy emphasized over speed. In the spatial configuration search, the distractor letter "L" was rotated by either 0°, 90°, 180°, or 270°, instead of always being upright as in Experiment 1. The experiment lasted for about 50 min. Other aspects of this experiment were identical to that of Experiment 1.

Results

As in Experiment 1, response accuracy and reaction time (RT) for correct trials were analyzed, with RTs

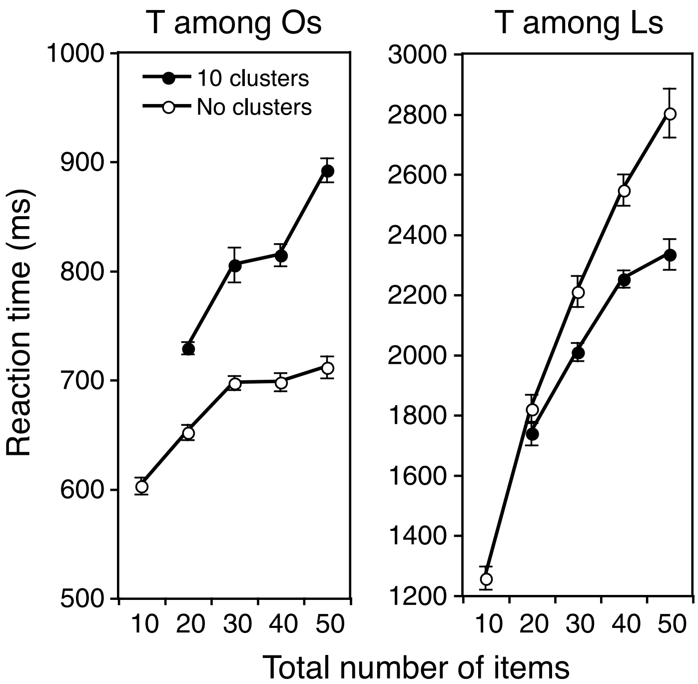

Figure 3. Reaction time data from Experiment 2. Compared to the control displays in which no cluster was present, clustering slowed down simple feature searches at all display sizes but facilitated the more difficult spatial configuration searches at larger display sizes. These results replicated the findings from Experiment 1 and showed that item clustering impacts different types of visual search differently. Error bars indicate within-subject standard errors.

analyzed without truncation (RT results are plotted in Figure 3). Because the size 10 display could be viewed both as a clustered display (with each cluster containing one item) and a non-clustered display (with ten evenly distributed items), this display condition was excluded from the overall analyses comparing the effect of search type, item clustering, and display size. Overall, there was a significant effect of search type in RT but not in accuracy ($F(1,15) = 634.94$, $p < 0.001$, and $F < 1$, respectively), showing that a spatial configuration search is more difficult than a simple feature search. The overall effect of item clustering was significant in RT and marginally significant in response accuracy ($F(1,15) = 9.14$, $p < 0.01$, and $F(1,15) = 3.48$, $p = 0.08$, respectively). Display set size effect was significant in RT but not in accuracy ($F(3,45) = 78.37$, $p < 0.001$; and $F < 1$, respectively). There was a two-way interaction in RT (significant) and accuracy (marginally significant) between search type and item clustering ($F(1,15) = 54.41$, $p < 0.001$; and $F(1,15) = 2.94$, $p = 0.11$, respectively), between search type and display size ($F(3,45) = 58.95$, $p < 0.001$; and $F(3,45) = 1.87$, $p = 0.15$, respectively), and between item clustering and display size ($F(3,45) = 4.27$, $p = 0.01$; and $F(3,45) = 2.63$, $p = 0.06$, respectively). There was also a three-way interaction in RT (significant) and in accuracy (marginally significant) among search type, item clustering, and display set size ($F(3,45) = 11.64$, $p < 0.001$; and $F(3,45) = 2.28$, $p = 0.09$, respectively), showing that the impact of item clustering differed for the two types of searches. Detailed analyses within each of the two search types were performed below.

Feature search for T among Os

Accuracy. The averaged response accuracy was 96.4%. For the non-clustered displays, the percent accuracies for display sizes 10 to 50 and SE were: 97.5 (0.4), 96.0 (0.6), 95.9 (0.8), 96.2 (0.7), and 96.7 (0.7), respectively. For the clustered displays, the percent accuracies for display sizes 20 to 50 and SE were: 96.6 (0.6), 95.2 (1.1), 96.3 (1.0), and 96.9 (0.9), respectively. Comparing the clustered and the non-clustered displays for sizes 20 to 50, there was no effect of item clustering or display size ($F < 1$).

RT. Comparing the clustered and the non-clustered displays for display sizes 20 to 50, there was an overall effect of item clustering and display size and a significant interaction between the two (all Fs > 10.67, ps < 0.001). In pairwise comparisons, the effect of item clustering was significant for every display size (all Fs > 28.35, ps < 0.001), such that search performance for the clustered displays was significantly slower than that for the non-clustered displays.

For the non-clustered displays (including the size 10 display), there was a significant display size effect ($F(4,60) = 31.40$, $p < 0.001$). Specifically, size 10 was faster than size 20, and size 20 was faster than sizes 30, 40, and 50 (all Fs > 17.44, ps < 0.001), with no difference among the latter three sizes ($F(2,30) = 1.19$, $p > 0.31$).

For the clustered displays, there was also a significant display size effect ($F(3,45) = 31.78$, $p < 0.001$). Specifically, display size 20 was faster than all the other display sizes and display size 50 was slower than all the other display sizes (all Fs > 16.28, ps < 0.001), with no difference between display sizes 30 and 40 ($F < 1$).

Spatial configuration search: T among rotated Ls

Accuracy. The averaged response accuracy was 95.7%. For the non-clustered displays, the percent accuracies for display sizes 10 to 50 and SE were: 97.2 (0.6), 95.2 (0.9), 95.8 (0.9), 96.4 (1.0), and 92.1 (1.3), respectively. For the clustered displays, the percent accuracies for display sizes 20 to 50 and SE were: 95.8 (0.7), 96.6 (1.0), 95.8 (1.1), and 96.7 (0.8), respectively. Comparing the clustered and the non-clustered displays for sizes 20 to 50, there was a marginally significant effect of item clustering ($F(1,15) = 4.88$, $p = 0.099$), such that accuracy was higher for the clustered than for the non-clustered displays. There was also a marginally significant effect of display size ($F(3,45) = 2.22$, $p = 0.099$) and a significant interaction between item clustering and display size ($F(3,45) = 3.45$, $p < 0.05$). Compared to the RT results reported below, there did not seem to be a speed and accuracy trade-off.

RT. Comparing the clustered and the non-clustered displays for sizes 20 to 50, there was an overall effect of item clustering and display size and a significant interaction between the two (all Fs > 7.93, ps < 0.001). In pairwise comparisons, while the effect of item clustering was not significant for display size 20 ($F(1,15) = 1.92$, $p > 0.18$), it was significant for all the other display sizes ($F(1,15) = 10.63$, $p < 0.01$ for display size 30; $F(1,15) = 18.91$, $p < 0.01$ for display size 40; and $F(1,15) = 28.58$, $p < 0.001$ for display size 50).

For the non-clustered displays (including the size 10 display), there was a significant effect of display size ($F(4,60) = 106.96$, $p < 0.001$). Specifically, size 10 was faster than size 20, size 20 was faster than size 30, size 30 was faster than size 40, and size 40 was faster than size 50 (all Fs > 6.55, ps < 0.05).

For the clustered displays, there was also a significant effect of display size ($F(3,45) = 55.45$, $p < 0.001$). Specifically, display size 20 was faster than size 30 and size 30 was faster than size 40 (Fs > 43.07, ps < 0.001). Sizes 40 and 50 did not differ from each other ($F(1.15) = 2.99$, $p = 0.10$).

Discussion

Compared to the non-clustered control displays, results from this experiment showed that clustering slowed down the simple feature searches at all display sizes but facilitated the more difficult spatial configuration searches at larger display sizes. These results replicated the findings of Experiment 1 and showed that clustering impacts different types of visual search differently.

General discussion

Together, results from two experiments showed that item clustering impaired a simple feature search but facilitated a difficult spatial configuration search. Why should this be the case? The fast and efficient feature search relies on parallel access to multiple item in the display (e.g., Treisman & Gormican, 1988; Treisman & Gelade, 1980; Wolfe, 1994). The presence of item clusters necessarily forms hierarchies within a display that can hinder direct and fast access to each item in the cluster. In other words, our visual system may be forced to localize each cluster first before it can access the item in a cluster. This may explain why the feature search slowed down when item formed clusters.[1]

On the other hand, in the demanding spatial configuration search, the presence of item clusters might have allowed observers to more easily mark off clusters that have already been visited and thus avoid repeatedly revisiting these clusters and reduce the number eye movements. It is also possible that clustering encouraged observers to fixate the center of mass of each cluster. As a result, on each fixation, items would be closer to fixation, increasing the rate of information extraction. In the non-clustered condition, items would be further from the fixation point on each fixation, resulting in a slower rate of information extraction. Consequently, search performance would be faster for the clustered than for the non-clustered displays. Although both of these hypotheses could explain how cluster formation can facilitate performance in the demanding spatial configuration search, studies measuring eye movement are needed to confirm them.

The impact of item clustering on search cannot be simply explained by a general item crowding effect (e.g., Levi, 2008). This is because the effect was present in the simple feature search even when items formed two-item clusters in Experiment 1. Moreover, the effect was in the opposite directions for the two types of searches examined here. Nevertheless, one may insist that crowding can play a bigger role in a simple feature search when items are largely encoded simultaneously from different spatial locations. That is, the presence of item clustering increases item crowding and makes it difficult to extract feature information from each item simultaneously. This account necessarily predicts that, if we simply manipulate crowding by manipulating item density, high-density displays should yield slower search performance than low-density displays. As discussed earlier, after controlling for eccentricity and item number, Cohen and Ivry (1991) found no effect of item density on feature search but an effect on conjunction search (i.e., slower search rate for high-density displays, opposite of what was found in the present study for spatial configuration searches). As such, item crowding does not provide a good explanation for the feature search results reported here. Instead, the presence of item hierarchy in clustered displays that forces search to access the cluster level before extracting the item information provides a better account for the present feature search results.

When a display contains clusters of item, a number of factors can influence the search performance. This includes the total number of items, the number of clusters, the number of items in a cluster, the item-to-item distance within a cluster, the center-to-center distance between the clusters, the edge-to-edge distance between the clusters, and the overall spatial extent of the display. While some of these factors can be manipulated separately, others co-vary and cannot be manipulated independently. The present study examined only some of these factors and future studies are needed to document the full extent of items clustering on visual search.

Although the present experiments only used letter stimuli, which have specific meanings, can the present results and conclusions apply to visual search for objects in general? In a lot of visual tasks, letters have been shown to be processed just like any other kind of objects.

For example, in visual short-term memory (VSTM) studies, Pashler (1988) used both letters and mirror-reversed letters and found comparable results for both. Similar results were reported in later studies by Luck et al. (e.g., Luck & Vogel, 1997; Vogel, Woodman, & Luck, 2001) when colored squares, bars, and other simple shapes were used. In the study by Alvarez and Cavanagh (2004), letters were explicitly considered as just another type of visual objects. In the visual search literature, many different types of visual stimuli have been used to study feature and conjunction searches (e.g., Treisman & Gormican, 1988; Treisman & Gelade, 1980; Wolfe, 1994). Results obtained with letters in feature and conjunction searches have not been shown to be qualitatively different from those obtained with other types of visual stimuli. Interestingly, in many of the published visual search papers using letters, the motivation for studying visual search is that we often need to search for a particular target object among distractor objects in our everyday lives. Thus, an implicit assumption in the visual search literature is that studying visual search using letters can help us understand how we represent and search for objects in the real world. From this regard, results from the present experiments on clustering using letters are likely to hold if other types of objects are used, and the present results are informative regarding how clustering may impact visual search for objects in the real world.

Given the prevalence of clustering in the everyday visual environment, the impact of clustering should be taken into account and understood if we want to fully understand how vision operates in the real world. Doing so will also allow us to actively manipulate clustering and enhance visual search performance in situations where such enhancement may be critical.

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Footnote

[1]Although the formation of item clusters may make it difficult to directly access the items in the cluster without first accessing the whole cluster, this type of hierarchical item structure is somewhat different from a holistic or highly integrated representation such as that seen in face perception. This is because the grouping between the items within a cluster is much weaker than what is present in a face.

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