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Individual differences in processing orientation and proximity as emergent features

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ABSTRACT

Numerous examples of meaningful inter-individual differences in visual processing have been documented in low- and high-level vision. For mid-level vision or perceptual organization, vision scientists have only recently started to study the inter-individual differences structure. In this study, we focus on orientation and proximity as emergent features and combine a quantitative information processing approach with an individual differences approach. We first replicated the results reported in Hawkins, Houpt, Eidels, and Townsend (2016) in a set of 52 observers. That is, observers showed higher processing capacity for detecting a change in a stimulus configuration when the emergent features orientation or proximity were changed. Next, we asked whether individual differences processing capacities were similar across emergent features. The capacity to detect *any* type of change correlated moderately across individuals, whereas the capacity to detect changes in either emergent feature alone was not strongly correlated. This indicates that there is no general sensitivity to emergent features and that observers can be good at detecting orientation changes whilst being poor at detecting proximity changes (and vice versa). An additional exploratory multivariate analysis of the data revealed that response times and accuracies correlated strongly within each emergent feature. Moreover, specific factors related to change detection and inward displacements were observed, revealing consistent individual differences in our data. We discuss the results in the context of the literature on individual differences in vision where both specific, fragmented factors as well as broad, general factors have been reported.

1. Introduction

Visual perception is frequently characterized as being the result of a linear, feed-forward process where a visual stimulus is decomposed into elementary sensations or features (e.g., spatial frequency, orientation, color). These features form the input for a cascade of processing steps where neurons become sensitive to increasingly complex stimulus features (Palmer, 1999; Wagemans, Wichmann, & Op de Beeck, 2005). One particular type of features, emergent features, consist of additional information beyond what is predicted from each component processed individually. The notion of emergence has played a central role in the Gestalt theory of perception (Hawkins et al., 2016; Wagemans et al., 2012). An important piece of evidence showing that the visual system processes these emergent features is the configural superiority effect. In an odd-quadrant paradigm, participants are faster and more accurate in selecting the odd-quadrant from a four-panel display when the components are presented together with a non-informative context that elicits the emergent feature compared to when the components are presented in isolation (Pomerantz & Cragin (2015); Pomerantz, Sager, & Stoever (1977)). This configural superiority effect is explained in terms of emergent features: when additional redundant information, albeit irrelevant in principle, is added to the components, new features emerge from the relationships between the visual components (Hawkins et al., 2016). Using this paradigm, several emergent features have been identified, amongst which proximity, orientation, linearity, symmetry and surroundedness (Pomerantz & Cragin (2015); Pomerantz & Portillo (2011)). Other studies have also addressed the neural basis of the configural superiority effect and the neural coding of emergent features (e.g., Costa et al., 2018; de-Wit, Kubilius, de Beeck, & Wagemans, 2013; Kubilius, Wagemans, & Op de Beeck, 2011).

Although this paradigm allows one to learn about the different kinds of emergent features, it does not allow to study how the different sources of

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information in the quadrants are processed. This was exactly the goal of the study of Hawkins et al. (2016). Here, the authors introduced a novel change detection paradigm where participants on each trial had to indicate whether the location of individual dots had changed or not. The dots could either be presented separately or together, and when together, the location change could imply a change in emergent feature (orientation or proximity, configural change) or not (control change). To assess information processing associated with configural and control changes, the authors relied on the Systems Factorial Technology framework (Townsend & Nozawa, 1995). This framework consists of a set of powerful nonparametric models and measures that enable researchers to quantify how different sources of information are combined in cognitive processing (Houpt, Blaha, McIntire, Havig, & Townsend, 2014). These different sources of information can originate from different modalities (e.g., auditory and visual information), or different stimulus properties within a modality. Systems Factorial Technology is broadly applicable and allows researchers to answer questions about four different aspects of processing: architecture, stopping rule, stochastic dependence and workload capacity (Houpt et al., 2014).

Hawkins et al. (2016) focused on workload capacity to assess information processing for emergent features. Workload capacity describes how the processing rate of each source changes as more sources of information are added. More specifically, it assesses how much information can be processed over time, while the amount of information is manipulated. The Systems Factorial Technology framework allows to qualitatively assess workload capacity by classifying the change in processing rates into three categories. Unlimited capacity refers to performance with no effect of the increased workload on processing of the individual sources, that is, the processing rate of the sources remains identical regardless of the workload. Limited capacity, on the other hand, describes a reduced performance on each source as the number of sources increases. Finally, super capacity occurs when performance on each source is better under higher workload, indicating that adding more sources increases the processing speed for individual sources (Houpt et al., 2014). The capacity coefficient is calculated by comparing performance with multiple sources of information with a baseline performance with each single source of information. The baseline for this comparison is that processing of multiple sources of information is unlimited capacity, independent and parallel. The capacity coefficient is described as the ratio of the performance when all sources of information are present to performance predicted from an unlimited capacity, independent, and parallel processing system. As a consequence, a capacity coefficient of 1 indicates unlimited capacity, a capacity coefficient greater than 1 illustrates super capacity and a capacity coefficient below 1 implies limited capacity (Houpt et al., 2014).

The results of Hawkins et al. (2016) showed that configural changes are indeed associated with higher capacity compared to control changes. This implies that configural changes are more efficiently processed compared to control changes, and that (changes in) emergent features elicit a different kind of processing compared to mere location changes. Interestingly, Hawkins et al. (2016) noted that there was high variation across individuals in the workload capacity measure. This made it difficult for the authors to use the capacity coefficient as an absolute measure of configurality for the different emergent features. However, this observation prompted our interest, as it leads to studying inter-individual variability in information processing for different emergent features (i.e., similar to Houpt & Blaha (2015) where individual differences in information processing for configural learning was assessed).

The study of individual differences is commonly associated with differential psychology where personality and intelligence have been extensively studied. This approach resulted in the formulation of the “Big Five” personality factors (Goldberg, 1990) and several theories regarding the structure of intelligence (Gardner, 1983; Spearman, 1904; Sternberg et al., 1985; Thurstone, 1938). In the spirit of early research on the *g* factor, Thurstone (1944) also studied the factorial structure of visual perception. Contrary to what had been observed in intelligence research, there seemed to be no general perceptual factor, but a set of different smaller factors each loading on a specific subset of tasks. Additionally, individual differences received attention from several vision scientists, including Pickford (1951) (color), Pirenne, Marriott, and O'Doherty (1958) (night vision, dark adaptation), Webster and MacLeod, 1988 (color matching), Sekuler, Wilson, and Owsley (1984) (contrast sensitivity), Coren and Porac (1987) (illusions), and Peterzell, Werner, and Kaplan (1995) (contrast sensitivity, color, infant visual development), to name a few. In contemporary vision science, however, this structural approach was, until recently, rare. Experimental rather than correlational data and analyses were the norm, and inter-individual variability was commonly regarded as measurement error, which could be discarded by averaging the responses of participants (Kanai & Rees, 2011; Mollon, Bosten, Peterzell, & Webster, 2017; Peterzell, 2016).

Over the last 10 years, however, research on individual differences in visual perception has witnessed a revival, initiated by Wilmer (2008) and culminating in several reviews (e.g., de-Wit & Wagemans, 2014; Mollon et al., 2017; Peterzell, 2016). Interestingly, this rapid growth has occurred almost entirely separately from the 80 + years of psychometric research examining visual perception and perceptual organization using correlational and factorial analyses of individual differences, which culminated in some extensive and classic reviews (Buckley, Seery, & Canty, 2018; Carroll, 1993; Lohman, 1979; Schneider & McGrew, 2012).

Among vision scientists, there has been (since Webster & MacLeod, 1988; Sekuler et al., 1984) a search to confirm or discover basic visual processes using individual differences. Some of these searches have involved investigations into possible general perceptual factors, with at best weak evidence for such general factors (e.g., Cappe, Clarke, Mohr, & Herzog, 2014; Bosten et al., 2017; Grzeczkowski, Clarke, Francis, Mast, & Herzog, 2017; Ward, Rothen, Chang, & Kanai, 2017), in line with the results obtained decades earlier by Thurstone (1944). Others have looked for specific factors related to underlying perceptual mechanisms or processes, with greater success in various domains. To name a few, contrast sensitivity (Peterzell & Teller, 1997; Peterzell et al., 1995), ensemble perception (Haberman, Brady, & Alvarez, 2015), motion perception (Takeuchi, Yoshimoto, Shimada, Kochiyama, & Kondo (2017)), visual illusions (Grzeczkowski et al., 2017), and face perception (Wilmer, 2017). Most of these studies have relied on a correlational approach, where performance on two or more tasks is computed for each individual and correlated. Associations are then taken to be caused by similar mechanisms, whereas dissociations are considered to be evidence for non-shared mechanisms. A rough summary of these studies is that variability in visual perception is highly specific, and few correlations are observed across tasks, except when they are highly similar.

Among psychometricians, there has also been a search to discover and confirm visual processes using individual differences, historically rooted in the study of the structure of intelligence. In contrast to vision scientists, these researchers have found broad general factors which span broad types of visual processing, and even link weakly to general cognitive ability (i.e., Spearman's g). They have also found a variety of specific factors mostly related to spatial processing and perceptual organization. As of today, there are over 25 specific factor-analytic components that have been discovered, including factors for some visual illusions, Gestalt properties, mental rotation, perceptual speed, etc. These studies have culminated in a multi-strata model of perceptual abilities (Buckley et al., 2018; Carroll, 1993; Schneider & McGrew, 2012). Although there have been few attempts to integrate these two vast and growing literatures (Peterzell, 2019), genuine integration and synthesis still seems to be lacking. Although the current study was primarily inspired by the dominant approach in the vision science literature (i.e., correlating performance on a few tasks), it will become clear that our results can also be interpreted in the context of the psychometric literature. As such, the current study potentially provides an initial step towards bridging both literatures.

Building on the recent study by Hawkins et al. (2016), the current study aimed to uncover individual differences in the processing characteristics of emergent features. To this end, participants performed a change detection task in which one or two dots could change location.

We hypothesised that if emergent features are processed more efficiently than local features, a change would be detected faster and more accurately when the change in location also involved a change in emergent feature (configural trials). Moreover, we used the capacity coefficient as a relative measure to assess workload capacity. We hypothesized that we would replicate the observations of Hawkins et al. (2016) in that the capacity coefficient would be larger, indicating better processing efficiency, in configural trials compared to control trials consisting of a change in the location feature only. However, our main goal was to quantify individual differences in processing efficiency of these emergent features and to see whether they would be correlated. This would indicate a general ability underlying stimulus integration, independent of the type of feature being manipulated. In order to answer these questions, we replicated the experiments reported in Hawkins et al. (2016) where processing efficiency associated with changes in orientation and proximity as emergent features was assessed.

2. Methods

2.1. Participants

52 psychology students from KU Leuven participated in exchange for two course credits. Participants (6 males and 46 females) were between 18 and 24 years old ($M = 19.05$, $SD = 1.44$) and had normal or corrected-to-normal vision. 6 participants were excluded from the analyses because they either failed to participate in both sessions or showed error rates above 30%. This cut-off score was based on previous work showing that the capacity coefficient measure becomes unreliable at error rates over 30% (Townsend & Wenger, 2004). All participants provided written informed consent before the start of the first session of the experiment. The experiment was approved by the local ethics committee (Social and Societal Ethics Committee).

2.2. Materials

The dot stimuli were created in Python 2.7.6 using the PsychoPy library (Peirce et al., 2019) and shown on a 24 inch monitor with a resolution of 1920 x 1200 pixels and a refresh rate of 60 Hz at a viewing distance of approximately 50 cm. The distance between the dots' inner contours was held constant at 1.10 degrees and each target dot was 0.74 degrees of visual angle away from the reference dot (illustrated in black on Fig. 1, panel a). Two types of dot stimuli were used, depending on the *type* of their location change: configural and control dot stimuli. For the configural stimuli, the location change included a change in perceived orientation. More specifically, after the change, the implicit line connecting the dots had an orientation of approximately 60 degrees away from the horizontal line. This degree of orientation change was based on the results of a pilot study conducted by Hawkins et al. (2016). As shown in Fig. 1, panel b, there were two variations of these configural stimuli: one where the left dot goes down and the right dot goes up, and vice versa. For proximity, the location change pertained to the proximity between dots in the configural condition (Fig. 2, panel b). More specifically, the initial distance between the reference dots was expanded with a factor of 1.72, which corresponds to a displacement of 0.52 degrees for each dot. This displacement was chosen in accordance with experiment 3 of Hawkins et al. (2016).

The control stimuli consisted of a location change without a change in emergent feature. Thus, for orientation, the implicit line between the dots remained horizontal. The four varieties of these control dots are illustrated in Fig. 1, panel c. For each of these double-dot stimuli, corresponding single-dot stimuli were presented as well: either on the left side or the right side. These dots could change to any of the four locations shown in Fig. 1, panel a. For proximity, the distance between their inner contours was kept at 1.10 degrees. The two varieties of these control stimuli are illustrated in Fig. 2, panel c. For each of these double-dot stimuli, corresponding single-dot stimulus location are shown in Fig. 2, panel a.

2.3. Procedure

The procedure of the experiment was based on the experiments reported in Hawkins et al. (2016). Participants were seated in a dark room with their head stabilized in a chinrest. Each trial started with a fixation cross presented for 240 ms at the center of the screen, followed by a blank display for 27 ms. On single-dot trials, a black dot was presented 0.72 degrees of visual angle either to the left or to the right of the center of the screen. On double-dot trials, two black dots were presented (one to the left and one to the right of fixation). This display was presented for 120 ms, after which a noise mask was presented for 240 ms. The target display was shown for 120 ms, followed by a white blank for 1880 ms, during which the participants had to respond whether a location change had occurred or not (Fig. 3).

At the beginning of the experiment, participants were instructed to press "N" (no change) on their keyboard if the target dots were in the same location as the reference dots and "C" (change) if the target dots' location had changed. During the first 20 practice trials, participants received feedback on their performance after each individual trial. If participants scored below 70% in this practice block, they were encouraged to repeat the 20 practice trials until their accuracy was above 70%.

During the actual experiment, participants completed a single session of 960 trials of the change detection task in six separate blocks. After each block, which lasted about eight minutes, they received a break with feedback on their performance. If they scored below 70%, the experimenter entered the room to motivate the participants to improve their accuracy in the next block(s).

The stimulus conditions in a specific block were randomly determined. However, over all blocks the stimulus conditions were distributed according to the equal stimulus rates design, a double factorial paradigm design that ensures that the inter-stimulus contingencies are zero, thereby reducing stochastic dependency (Houpt et al., 2014). More specifically, there were 25% no-change trials, 25% double-dot changes (either configural or control) and 50% single-dot changes.

The emergent features orientation and proximity were run in separate sessions, such that participants completed either the orientation or proximity session on one day, and the other experiment when they returned. Because both sessions are almost exactly the same, we report it here as a single experiment run in two sessions.

2.4. Data analysis

We used R[1] for all our analyses. All analyses were performed in RStudio (RStudio Team, 2018). All code and data to reproduce the results we report in this paper can be found on the Open Science Framework: https://osf.io/vgxja/. We first report the same analyses as conducted by Hawkins et al. (2016) before reporting the individual differences analysis.

As mentioned in the Participants section, 6 participants were removed prior to analyzing the data. 3 participants failed to reach an

[1] We relied on R (Version 3.6.1; R Core, 2019) and the R-packages *BayesFactor* (Version 0.9.12.4.2; Morey & Rouder, 2018), *coda* (Version 0.19.3; Plummer, Best, Cowles, & Vines (2006)), *cowplot* (Version 1.0.0; Wilke, 2019), *dplyr* (Version 0.8.3; Wickham, François, Henry, & Müller, 2019), *ez* (Version 4.4.0; Lawrence, 2016), *fda* (Version 2.4.8; Ramsay, Wickham, Graves, & Hooker (2018)), *forcats* (Version 0.4.0; Wickham & Henry, 2019a), *ggplot2* (Version 3.2.1; Wickham, 2016), *ggthemes* (Version 4.2.0; Arnold, 2019), *gridExtra* (Version 2.3; Auguie, 2017), *HDInterval* (Version 0.2.0; Meredith & Kruschke, 2018), *Matrix* (Version 1.2.17; Bates & Maechler, 2019), *papaja* (Version 0.1.0.9842; Aust & Barth, 2018), *purrr* (Version 0.3.3; Henry & Wickham, 2019a), *readr* (Version 1.3.1; Wickham, Hester, & Francois, 2018), *sft* (Version 2.2.1; Houpt et al., 2014), *stringr* (Version 1.4.0; Wickham, 2019b), *SuppDists* (Version 1.1.9.4; Wheeler, 2016), *tibble* (Version 2.1.3; Müller & Wickham, 2019), *tidyr* (Version 1.0.0; Henry & Wickham, 2019), and *tidyverse* (Version 1.2.1; Wickham, 2017).

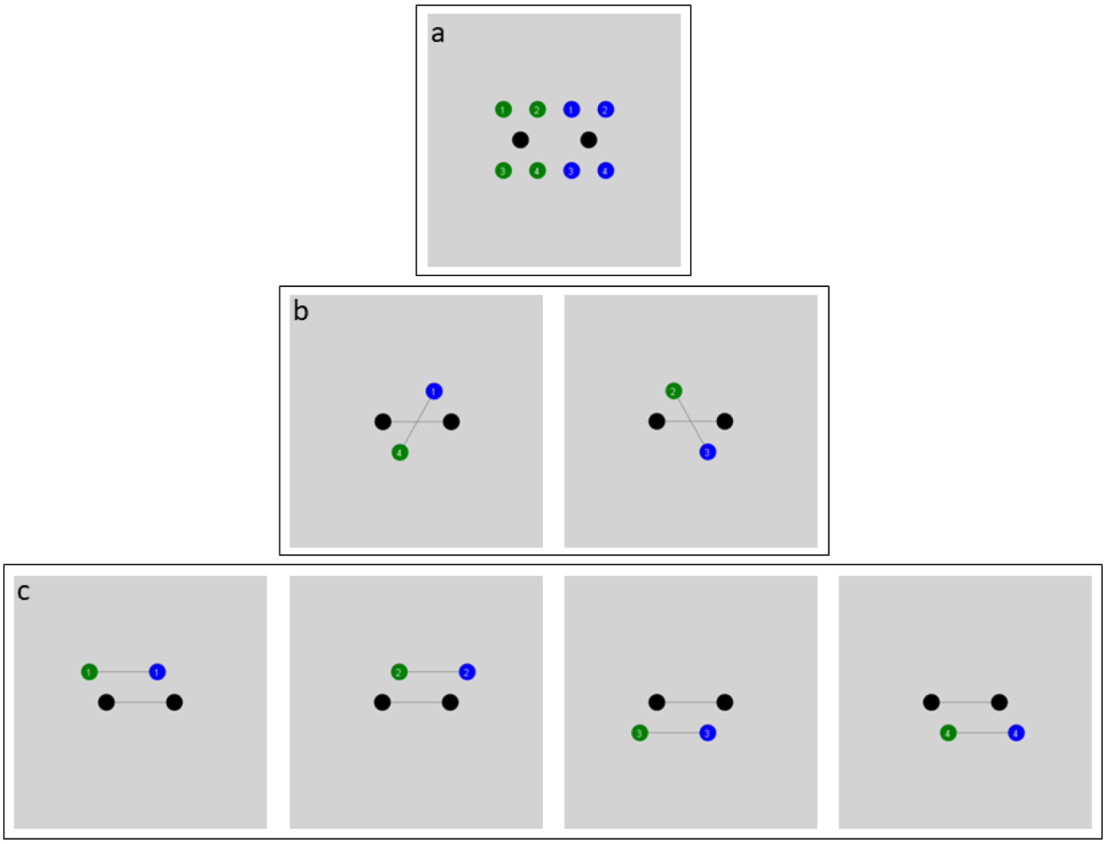

Fig. 1. (a) Possible locations of the dots for orientation as an emergent feature. (b) Two configural trials in which the location change is accompanied by a change in orientation. (c) Four control trials in which location changes, but orientation stays the same. Black dots are the reference dots, green and blue dots are the possible target dots for the left and right channel, respectively. Lines are printed for clarity only and were not depicted in the actual experiment. During the experiment, all dots were black.

accuracy of 70%, 2 participants did not return for the second session, and 1 participant decided to quit during the experiment. Mean response times were computed based on the correct responses only. For the analysis of mean response times and accuracies, we computed Bayes Factors (BFs) to summarize how well the data were predicted by a range of competing models (i.e., the presence/absence of a main effect of condition). We adopted Jeffrey's guidelines to interpret the values of these BFs: BFs between 1 and 3 are considered to be anecdotal evidence for one model over the other, whereas a BF between 3 and 10 indicates substantial evidence. BF > 10, BF > 30 and BF > 100 are regarded as strong, very strong and decisive evidence, respectively (Jarosz & Wiley, 2014). As will become clear, for our results, these criteria did not matter a lot. To compute the capacity z-score, we relied on the *sft* R package (Houpt et al., 2014) in which the theoretical work by Houpt and Townsend (2012) is implemented. For the analysis of the capacity z-score, we used Bayesian t-tests as introduced by Rouder et al. (2009) and implemented in the BayesFactor R package (Morey & Rouder, 2018).

As we only had a single measurement occasion for each capacity score, we could not resort to computing test–retest reliability for capacity scores. Thus, we decided to compute reliabilities by a split-half procedure where we split the data set, for each participant separately, in half. For each half, we then computed the capacity scores for each participant. This results in two capacity scores (i.e., for each half) for each participant for each unique condition (i.e., the two-by-two combination of orientation/proximity and control/configural). For each unique condition, we then computed the correlation between capacity scores derived from each half. Because a data set like ours can be split in many arbitrary ways, we decided not to compute this correlation once, but to do it many times, each time based on a different (but equally balanced) split of the data. In our case, we ran this procedure a 1000 times, and thus obtained 1000 reliability estimates for each capacity score. Because computing split-half reliability effectively halves the number of measurements on which the correlations are based, it is possible to apply the Spearman–Brown prediction formula to estimate what the correlation would be if the "test length" (i.e., the experiment in this case) was doubled again. Thus, for each distribution of correlations, we applied this formula to arrive at the final distributions of correlation estimates. The resulting distributions served as a benchmark for how strongly the observed correlations between capacity scores on each emergent feature would be attenuated by their individual reliabilities.

3. Results

3.1. Orientation

Mean response times and accuracies for the double-dot trials are depicted in Fig. 4, panel a and b. The BF analysis showed decisive evidence for the main effect of condition on response times over the empty model containing only subject variability (BF = 1.63e + 69). The mean posterior decrease in response times in configural trials was 45.30 ms (95% HDI = [39.11, 51.57]) compared to control trials and 59.08 ms (95% HDI = [52.12, 66.18]) compared to no change trials. For accuracy, there was decisive evidence for a main effect of condition over the subject only model (BF = 1.21e + 29). On average, participants had a slightly higher accuracy in configural than control trials (mean accuracy difference = 0.03, 95% HDI = [0.03, 0.04]) and no change trials (mean accuracy difference = 0.04, 95% HDI = [0.04, 0.05]).

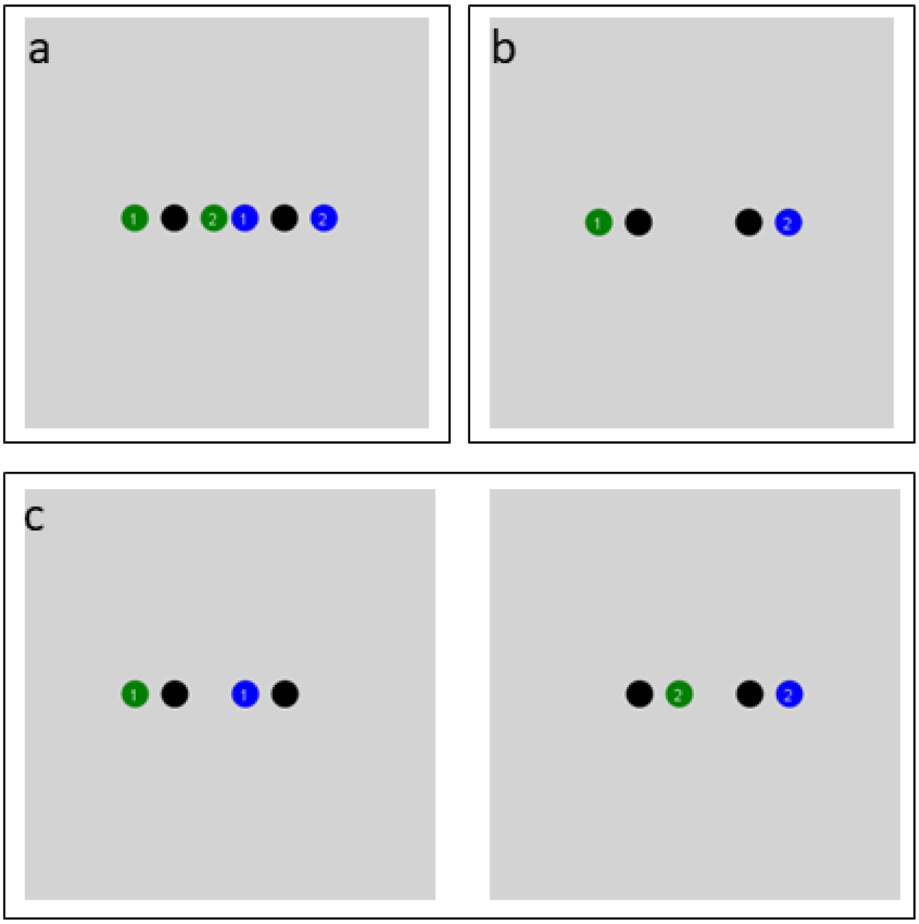

Fig. 2. (a) Possible locations of the dots for proximity as an emergent feature. (b) Configural trial in which the location change is accompanied by a change in proximity. (c) Two control trials in which location changes while proximity stays the same. Black dots are the reference dots, green and blue dots are the possible target dots for the left and right channel, respectively. During the actual experiment, all dots were black.

The capacity z-score (Cz) was used as a summary statistic for the capacity coefficient (see Fig. 4, panel c). A Cz of zero indicates unlimited capacity, below zero means limited capacity and above zero reveals super capacity. A Bayesian t-test indicated that the mean Cz was higher in the configural condition compared to the control condition (BF = 3.44e + 08). The mean posterior difference between Cz in configural and control trials was 3.17, with a 95% HDI between 2.49 and 3.90. Note that the mean capacity z-score of both conditions was negative, indicating limited capacity in both configural and control trials.

3.2. Proximity

Mean response times and accuracies for the double-dot trials are shown in Fig. 5 (panels a and b). The BF analysis showed decisive evidence for the main effect of condition on response times over the subject only model (BF = 1.88e + 276). The mean posterior decrease in response times in configural trials was 106.46 ms (95% HDI = [100.30, 112.65]) compared to control trials and 99.89 ms (95% HDI = [92.68, 106.96]) compared to no change trials. There was decisive evidence for condition as a main effect over the subject only model (BF = 7.41e + 71) for accuracy as well. On average, participants had a slightly higher accuracy in configural than control trials (mean accuracy difference = 0.08, 95% HDI = [0.07, 0.09]) and no change trials (mean accuracy difference = 0.06, 95% HDI = [0.05, 0.07]).

For Cz (Fig. 5, panel c), a Bayesian t-test indicated that the configural and control conditions differed in Cz (BF = 1.46e + 07). The posterior difference between both conditions was 4.32 (95% HDI = [3.16, 5.48]) favouring the configural trials. Although most participants showed negative Cz, a marked proportion of participants also showed positive Cz for the configural condition.

3.3. Individual differences

Emergent features, more specifically orientation and proximity, seem to provide additional information beyond the mere location feature in a two-dot display. As was already mentioned by Hawkins et al. (2016), there is pronounced inter-individual variability in processing efficiency (i.e., Cz scores). In this analysis, we were interested to examine how these individual differences correlate across different emergent features. The Pearson correlation coefficient was used to assess the linear relationship between Cz scores across emergent features. In configural trials, we observed no correlation between the Cz scores for orientation and proximity in the configural trials (r = 0.16) (Fig. 6, panel a). In contrast, there was a moderate correlation between Cz for orientation and proximity in the control trials of both experiments (r = 0.40) (Fig. 6, panel b). BFs indicated evidence for a positive correlation in the control condition (BF = 10.20), but not for the configural condition (BF = 0.55). In addition, we computed the correlation between the differences in Cz for control and configural for orientation and proximity. This correlation quantifies whether changes in Cz (i.e., how much Cz changes for configural compared to control stimuli) correlate across emergent features. This correlation turns out to be similar to the one for configural trials (r = 0.22, BF = 0.83). Although the numerical value of this correlation is higher, it seems to be influenced by the outlying data points (Fig. 6, panel c). Indeed, the Spearman correlation is much lower (r = 0.08), whereas this is not the case for configural trials (r = 0.16). These findings suggest rather independent mechanisms underlying the processing of the emergent features tested here.

3.3.1. Reliability

The split-half reliability of the Cz scores was estimated using a simulation-based procedure. In Fig. 7 the results are visualized (summary in Table 1). After applying the Spearman-Brown correction, all

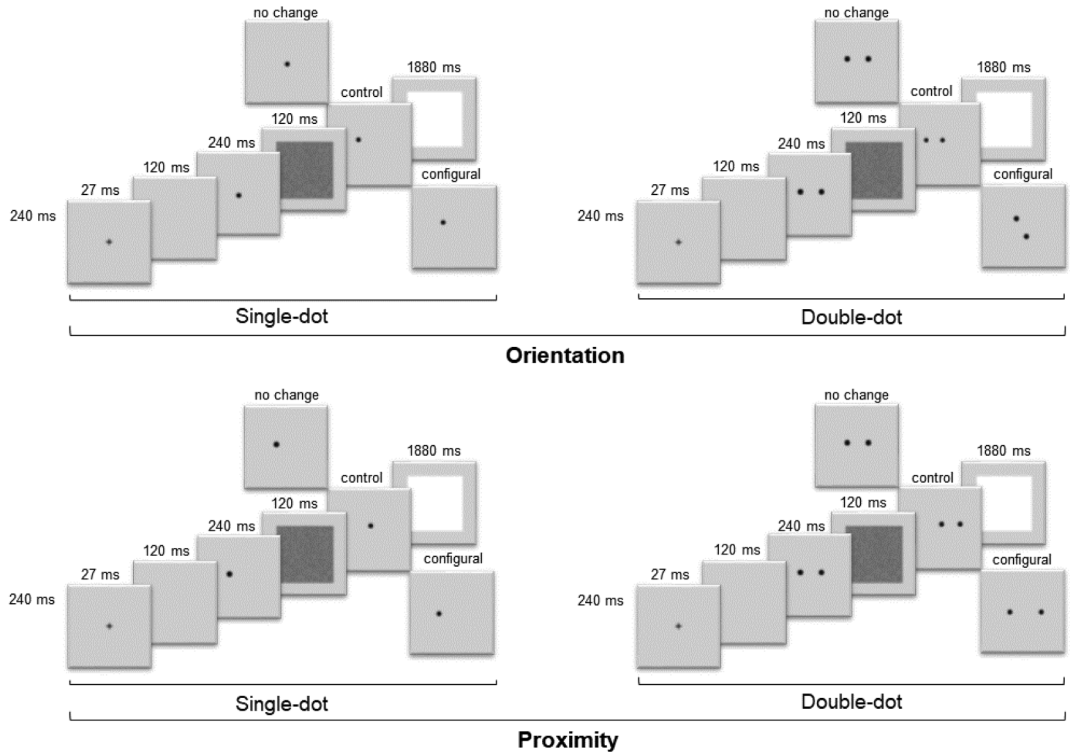

Fig. 3. Procedure of the experiment. Participants saw a fixation cross for 240 ms, followed by a very brief blank (27 ms). The reference dot (single-dot trials) or dots (double-dot trials) were presented for 120 ms, followed by a 240 ms Gaussian noise mask. The dot or dots were again displayed for 120 ms, after which the participant had to answer. The dots could either be in the same location as compared to the reference dots (no change), a different location (control change) or a different location with a change in emergent feature (configural change). For the single-dot stimuli, the control and configural labels refer to the positions associated with the double-dot stimuli.

estimated reliabilities are higher than .75 which implies that reliability is adequate but not perfect. Nevertheless, this implies that the correlations we observed are not due to poor reliability of our measures (i.e., correlation attenuation is not too strong).

3.4. Exploratory analysis

In this section, we report an additional analysis we did not plan to do initially, but we decided to include it here based on an insightful comment by one of the reviewers. That is, in the previous analysis we reported a very focused analysis of some pairwise correlations. However, it may also prove to be interesting to look at the general multivariate structure of mean response times and accuracies for all stimuli, together with the capacity coefficients. Such an approach has the potential to reveal general factors that might be underlying the data (Peterzell, 2016) rather than the very specific ones we have been looking into in the previous section. In the next section, we report on some potential factors we derived from the general correlation matrix

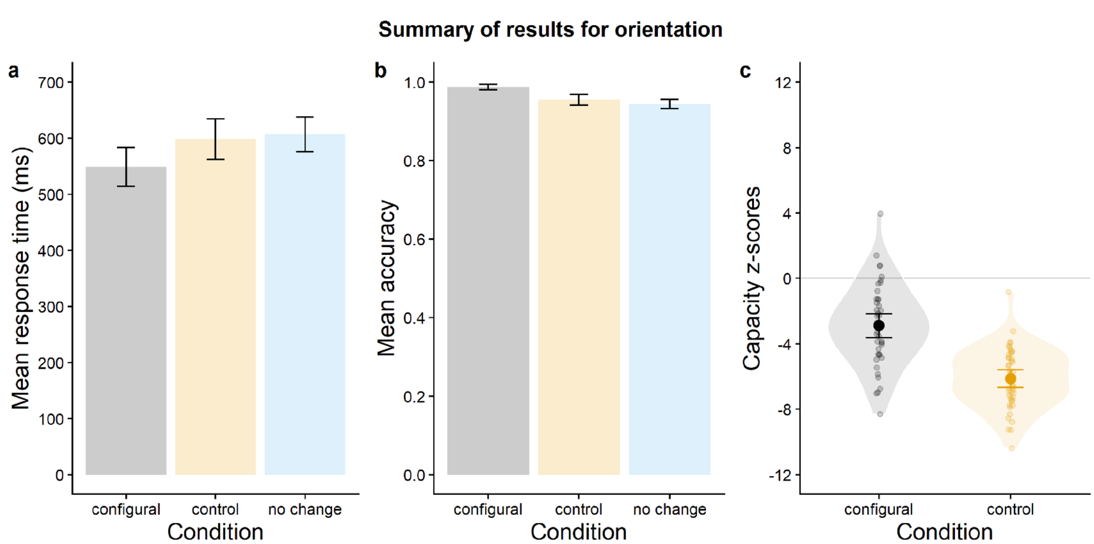

Fig. 4. Summary of results for orientation. (a) Mean response times for double-dot trials. (b) Mean accuracy for double-dot trials. (c) Capacity z-scores. Positive numbers indicate super capacity, whereas negative numbers indicate limited capacity. In general, higher numbers illustrate more efficient processing of the stimuli. Error bars indicate mean +/- 2 SEM.

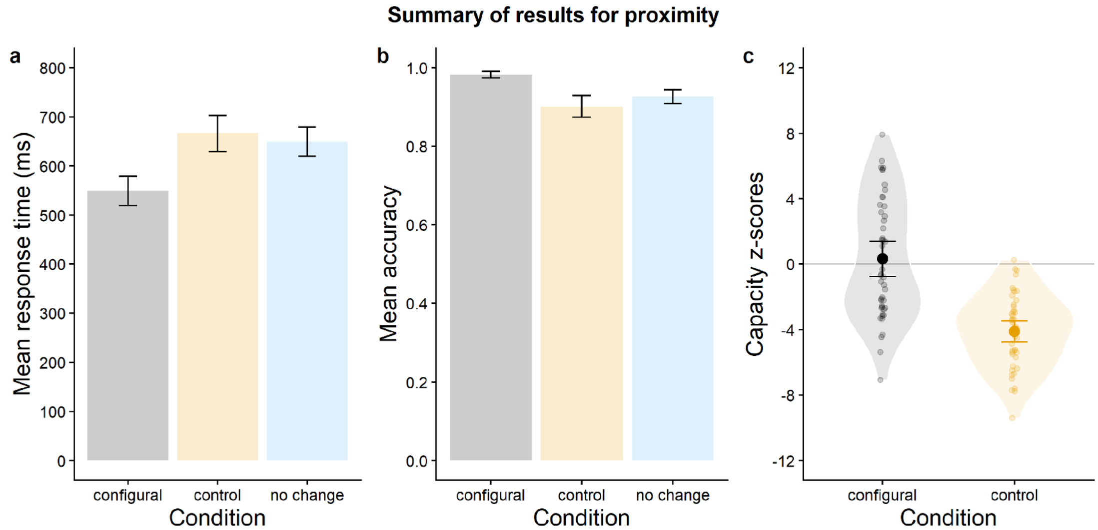

Fig. 5. Summary of results for proximity. (a) Mean response times for double-dot trials. (b) Mean accuracy for double-dot trials. (c) Capacity z-scores. Positive numbers indicate super capacity, whereas negative numbers indicate limited capacity. In general, higher numbers illustrate more efficient processing of the stimuli. Error bars indicate mean +/- 2 SEM.

of all dependent variables. Furthermore, we consider the specific correlation matrix of all capacity coefficients. The interested reader is referred to the Appendix to inspect the correlation matrices of response times and accuracies in more detail (the numerical versions of the correlations matrices can be found at https://osf.io/ht4qd/).

3.4.1. *Correlation matrix of all dependent variables*

In Fig. 8, the pairwise correlations between all dependent variables are depicted. An initial inspection immediately reveals structured positive and negative dependencies between different variables. For mean response times, two clusters are discernible, one pertaining to orientation and the other to proximity. Interestingly, within these clusters some finer structure can also be discerned. For example, for orientation the no-change vs. change trials cluster together. This is similarly so for proximity, yet in the change trials, there is even further clustering. Interestingly, the two stimuli where either the left or the right dot changed in the inwards direction correlate more strongly with each other than with all other change trials for proximity. Thus, for response times orientation and proximity show separate factors, and there seems to be a *change detection factor*. That is, change and no-change trials dissociate to some extent. At an even more fine-grained level, proximity trials with inwards stimulus displacements dissociate slightly from other change trials. Correlations between accuracies show less clear, but equally interesting structure compared to mean response times. A large chunk of positive correlations is clustered around the orientation stimuli, similar to the pattern for mean response times. Interestingly, however, all no-change orientation and proximity stimuli mix here in a second cluster. Thus, for accuracies a similar change detection factor emerges as well. Accuracies for inward displacements are clustered together again, as are accuracies for all other proximity stimuli. In sum, a similar picture seems to emerge as for mean response times. There are separate factors for orientation and proximity, there is a change detection factor across emergent features, and an inward displacement factor for proximity.

3.4.2. *Capacity coefficient correlations*

The correlations for the capacity coefficients depicted in Fig. 9 show a more nuanced picture of our main results for the correlation between orientation and proximity. Almost all correlations are in between the correlation for configural stimuli and the one for control stimuli (i.e., those reported earlier). In general, it is not surprising that capacities for configural and control stimuli correlate to some extent within emergent features. That is, emergent features are here quantified by a change in capacity coefficient. If such a change is present in the same direction in all individuals, it should follow that both capacity coefficients are correlated to some extent. We interpret the pattern of correlations as an indicator that there might be evidence for some kind of general capacity factor, but given the size of the correlations, we consider it to be a mere indication that deserves to be followed up in future research.

4. Discussion

The goal of this study was twofold. First, we wanted to assess the replicability of the results reported in Hawkins et al. (2016). Inspired by

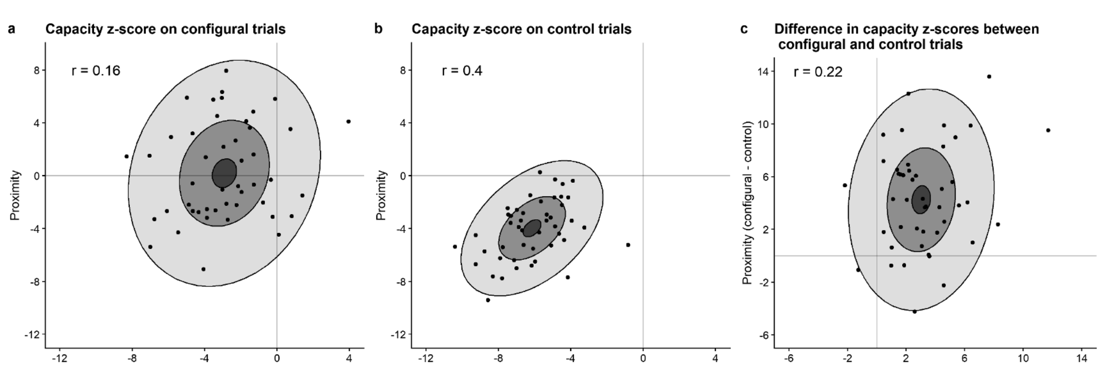

Fig. 6. Scatter plots comparing capacity z-scores in (a) configural and (b) control trials for orientation and proximity and (c) for the difference between configural and control trials for orientation and proximity. Pearson correlation coefficients are displayed in the upper left corner.

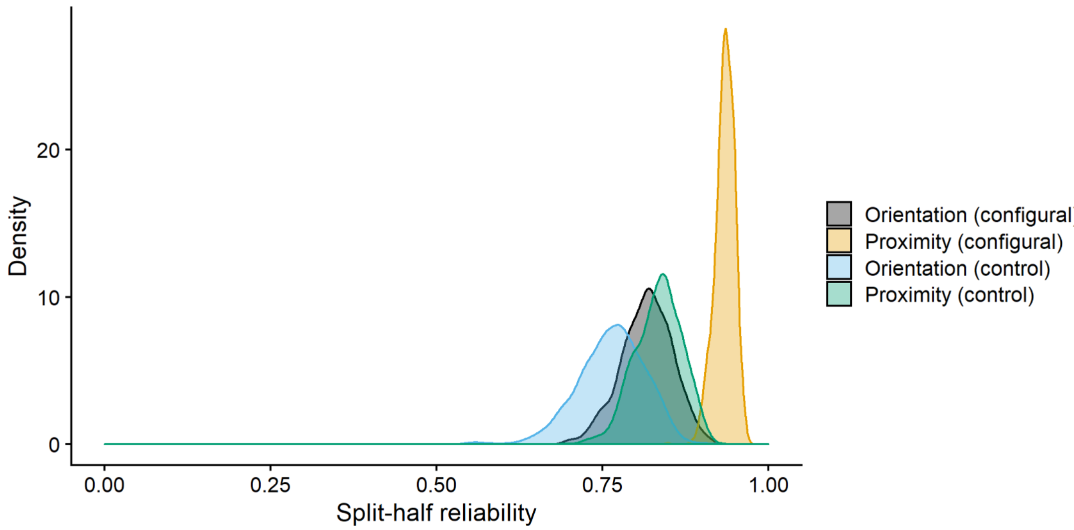

Fig. 7. Split-half reliabilities for all capacity z-scores.

Table 1
Split-half reliabilities for the capacity coefficients.

Measure	Mean r	95% CI lower bound	95% CI upper bound
Orientation (configural)	0.82	0.74	0.89
Proximity (configural)	0.93	0.90	0.96
Orientation (control)	0.76	0.66	0.85
Proximity (control)	0.83	0.76	0.90

Note. The reliabilities were corrected using the Spearman–Brown formula. Lower and upper bounds refer to the 2.5% and 97.5% quantiles of the distribution obtained after simulation (1000 iterations).

the substantial inter-individual variability in workload capacity for both orientation and proximity, we asked whether information processing would correlate across these tasks. That is, do individuals process these emergent features similarly or is there a dissociation already at this very basic level of stimulus processing?

With respect to the first goal, our results are strikingly similar to those obtained by Hawkins et al. (2016). The location change in the configural and control conditions was identical, yet, response times, accuracy and capacity z-scores were all better in the configural than the control trials. This indicates that the dots are processed more efficiently when there was a change in emergent feature, more specifically orientation and proximity, in addition to the change in location. In sum, for both emergent features, we very clearly replicated the results obtained by Hawkins et al. (2016).

Hawkins et al. (2016) already devoted some discussion to this, but it is worth reiterating here that the capacity scores were not uniformly positive in the configural condition. For orientation, most individuals showed limited capacity, and some individuals showed super capacity. For proximity, participants showed limited capacity on average, yet many participants had a capacity z-score above 0 in the configural condition, indicating super capacity. On average, these results imply less efficiency for configural trials compared to when local features are processed in parallel and independently (equal efficiency would result in a capacity score of zero). One consequence of this finding is that the capacity score can not be used as an absolute measure of configural processing. Indeed, it should always be interpreted relative to a control condition in which location changes, yet the emergent feature under study does not. Second, it reveals the task-specific nature of the capacity measure. Although the control condition yielded consistently negative capacity scores for both emergent features, capacity scores were considerably higher (on average) for proximity compared to orientation. This might come across as counterintuitive because one could derive from Figs. 1 and 2 that the orientation change is much less subtle compared to the location change for proximity. Why then do we observe higher scores for proximity compared to orientation? It turns out that the single-dot trials are crucial to interpret this difference. In Fig. 10, response times and accuracies for the single dot trials are visualized. Although there is only a small difference in response times, the accuracy difference is clear. It seems to be the case that detecting a location change along the same (horizontal) axis is much more difficult, compared to the type of location changes in the orientation task. This has a small, but apparently non-negligible influence on the capacity scores, as they are higher for proximity rather than orientation. Thus, in this type of experiment, it is not possible to compare the absolute values of the capacity scores of the configural condition for both emergent features, because the single-dot trials are not matched in difficulty. Although not strictly necessary for the current purposes, it might still be worthwhile for future studies to look into this, and to try to equate the difficulty of these single-dot trials. One potential way of achieving this is by manipulating the axis at which the initial reference dots appear.

Regarding our second goal, we indeed observed considerable inter-individual variability in capacity scores, as did Hawkins et al. (2016). However, the correlation between the individual differences in the configural conditions for orientation and proximity was, at best, weak. Indeed, the Bayes factors for the correlations for configural trials and differences in Cz scores indicated that the data cannot discriminate between the presence or absence of a correlation. Consequently, this analysis suggests that these emergent features might not rely on the same underlying integration mechanism, but could be processed in separate channels. This conclusion is corroborated by the results of the multivariate analysis of mean response times and accuracies. Separate factors for orientation and proximity emerged here as well. A moderate correlation was observed for the control condition where location changes occurred yet without an associated change in emergent feature. To us, this indicates that the weak correlation in the configural condition can not be explained by a general absence of the ability to detect any meaningful correlation. Indeed, it makes sense that the ability to detect a "mere location change" does generalize across stimuli that are different (but still quite similar). Thus, it seems we were able to pick up on meaningful variability in detecting location changes, but this did not generalize to correlated variability in the capacity for processing emergent features. A second aspect that convinced us our data set allowed us to detect meaningful correlations for capacity scores was that the split-half reliability of the capacity measures was quite high. Although it is not uncommon to observe good reliability scores in experimental paradigms (Cappe et al., 2014; Grzeczkowski et al., 2017), reliability of dependent variables in experiments is not always guaranteed (Hedge, Powell, & Sumner, 2018). Speculatively, this high reliability for capacity scores might be due to the fact that we rely on a model-based individual difference measure, rather

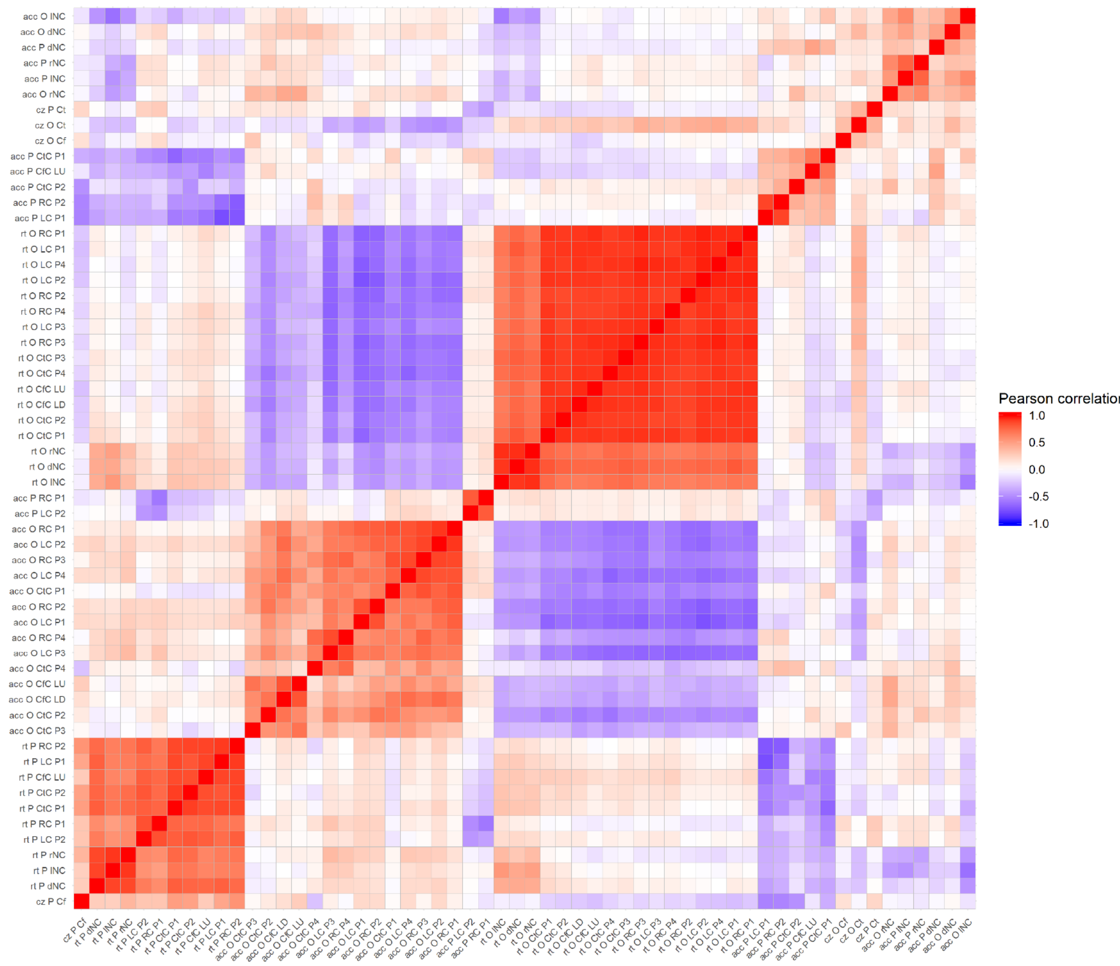

Fig. 8. Correlation matrix for all dependent variables. The description denotes the dependent variable, specific stimulus or condition as well as whether it was an orientation or proximity task. rt, acc, and cz refer to response times, accuracies and capacity coefficients, respectively. O and P refer to orientation and proximity. CfC (configural change), CtC (control change), dNC, lNC, rNC (double, left, and right no change), LC and RC (left and right change) refer to the specific type of change. LD and LU (left down and up) and P1 to P4 (position 1 to 4) refer to the specific change in position for a particular trial. The ordering of the variables was determined by hierarchical clustering using the complete linkage method, which aims to find similar clusters.

than a common statistic of response times (e.g., the mean or the median). As this measure is supposed to reflect something genuine about an individual's information processing system, it might be the case that this measure is more robust to slight variations in the dependent variable under consideration (i.e., response times in this case).

In an additional analysis, we explored the multivariate structure of mean response times and accuracies for all different trial types, as well as for all capacity scores. For mean response times and accuracies, this analysis revealed that there are separate factors for the orientation and proximity tasks, corroborating our observation on the weak correlation between capacity scores for orientation and proximity on configural trials. Furthermore, we observed a change detection factor and a factor for detecting inward positional displacements. Apart from being informative for our research questions, this analysis also proved to be fruitful for discovering unanticipated factors related to the task used (i.e., change detection) or specific stimuli used (i.e., inward displacements for proximity stimuli).

The results of this study can be discussed in the context of the recent vision science literature as well as the recent psychometrics literature. For vision science, the results seem to be consistent with studies where the main conclusion is that performance on many visual tasks is at best weakly correlated, and if it is correlated, the tasks are highly similar or obviously measuring the same phenomenon (Cappe et al., 2014; Grzeczkowski et al., 2017; McGovern, Walsh, Bell, & Newell, 2017). In our case, one can reliably measure individual differences in processing the emergent features orientation and proximity, but they do not seem to tap into the same underlying mechanisms. Stated differently, there is no *general ability* for detecting emergent features. Rather, there are many emergent features, and individuals might be good at processing one, while bad at processing another.

With respect to the psychometrics literature, can our results be interpreted in the context of the framework on spatial ability presented by Buckley et al. (2018)? In their framework Buckley et al. (2018) rely on the Cattell-Horn-Carroll theory of cognitive factors discussed in Schneider and McGrew (2012), and specifically focus on the visual processing factor (Gv). Based on the results of the simple pairwise correlations, as well as the exploratory multivariate analyses, we speculate that the orientation task mostly relies on the factors Spatial Orientation, Speeded Rotation, and Movement Detection. That is, these are all relevant processes for the single- and double-dot trials in the orientation task. In contrast, for the proximity task, we speculate that a single factor called Length Estimation might be primarily driving the individual differences (although Movement Detection could in principle also contribute). That is, for double-dot trials, estimating the distance (i.e., proximity) between the dots is sufficient for performing the task. Analogously, for single-dot trials, this could happen by estimating the distance relative to fixation. For the more specific change detection factor, we assume Movement Detection might be the best fitting underlying factor. Last, the factor for detecting inward vs. outward positional displacements does not fit in any of the factors described by

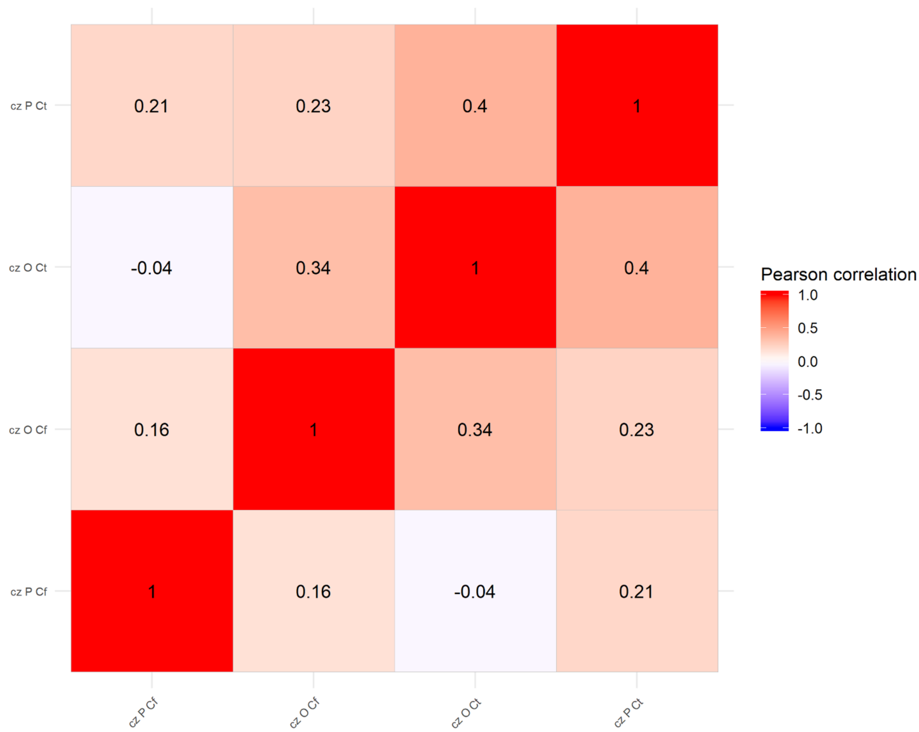

Fig. 9. Correlation matrix for capacity coefficients. The description denotes the dependent variable, specific stimulus or condition as well as whether it was an orientation or proximity task. cz refers to capacity coefficient. O and P refer to orientation and proximity. Cf refers to configural trials, and Ct to control trials. The ordering of the variables was determined by hierarchical clustering using the complete linkage method, which aims to find similar clusters.

Buckley et al. (2018), but it does reflect findings from vision science studies on expanding vs. contracting motion. That is, observers are better at detecting motion away from fixation than toward fixation (Ball & Sekuler, 1980). Furthermore, observers show more efficient visual search for an expanding target in a set of contracting distractors compared to searching for a contracting target in a set of expanding distractors (Takeuchi, 1997). Last, neuropsychological evidence indicates that contracting objects show more visual extinction compared to looming objects (Dent & Humphreys, 2011). Thus, this last, specific, fine-grained factor seems consistent with the literature on motion processing. Of course, we have to stress that a discussion of our results in the context of these visual factors is purely based on intuiting how well these factors encompass our behavioral tasks. Validation studies are necessary to assess whether tasks such as the one used here effectively load on the factors we suggested earlier in this paragraph. That is, future studies should assess whether performance on standardized tasks that strongly load on Spatial Orientation, Speeded Rotation, Movement Detection, and Length Estimation cluster together with performance on the orientation and proximity tasks used here.

A potential alternative explanation for our results is that, in fact, there is a strong correlation between processing orientation and proximity, but our design was not suited to reveal such a correlation. That is, in this study, capacity for orientation and proximity was always assessed in a blocked manner, counterbalanced across participants (i.e., first session was either orientation or proximity, and the other task in the second session). Our reliability analysis showed that capacity scores are robust within sessions, but they might show day-to-day variability (i.e., state-like behavior as in Wexler, Duyck, & Mamassian (2015) or Wexler (2018)) rendering the correlation between orientation and proximity virtually nil. This type of reasoning could be motivated by the relatively poor test–retest reliability that is

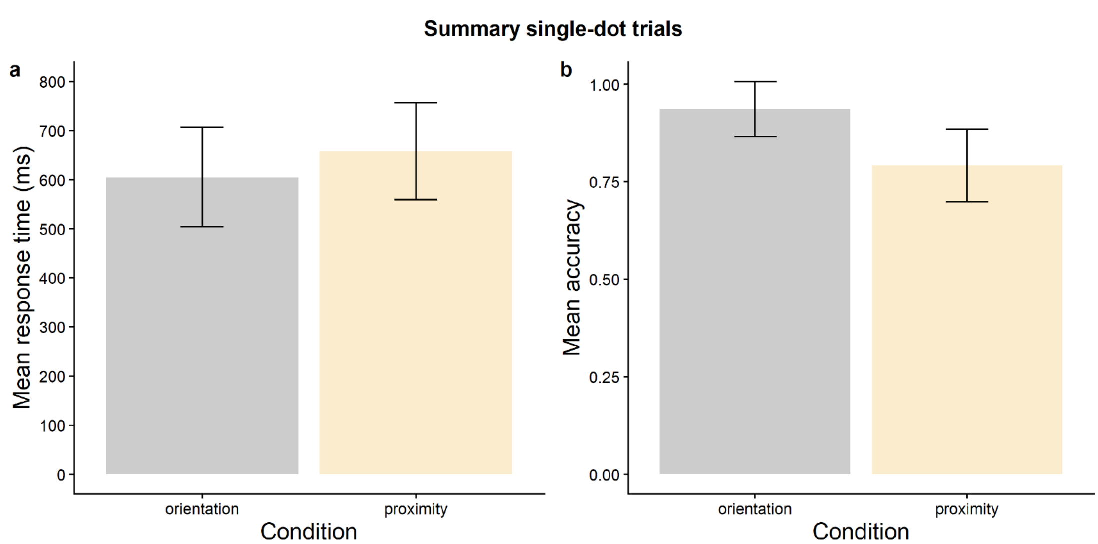

Fig. 10. Summary of results for single-dot trials. (a) Mean response times for both emergent features. (b) Mean accuracies for both emergent features. Error bars indicate mean +/- 2 SEM.

commonly observed for experimental measures (Enkavi et al., 2019; Hedge et al., 2018). This could be addressed by measuring capacity for orientation and proximity within the same experimental session, and repeating this in a second experimental session. Based on the work of Rouder and Haaf (2019) however, we predict that such a design would reveal stability of the capacity coefficients. That is, for experimental measures it has been shown that average or poor test–retest reliability stems from measurement error in the measure, rather than genuine inter-individual variability across sessions. Hierarchical modeling of these measures can be used to take measurement error into account, and this approach has revealed that most of the experimental measures show high test-retest reliabilities (i.e., correlations > .9). Thus, although an explanation of the absence of a correlation based on day-to-day variability of capacity coefficients still needs to be empirically ruled out, we believe that the literature provides a sufficiently compelling argument for why this would not be the case.

Systems Factorial Technology is an information processing framework that includes measures beyond workload capacity. Future studies could rely on these additional measures to uncover the specific mechanisms underlying the processing of emergent features. Indeed, it might be that workload capacity does not show a correlation across emergent features, but other measures such as the mean interaction contrast or the survivor interaction contrast do show one. For this, a saliency manipulation (saliency of the change of emergent features) would be required. This type of study would allow one to characterize not only workload capacity, as was done in the current study, but also processing architecture and stopping-rule. In general, we believe the Systems Factorial Technology framework is very versatile, allowing for numerous experimental manipulations, that open up new avenues for studying emergent features. Moreover, the design of the current study is very easy to adapt and allows for additional manipulations that could strengthen the conclusions from this study. Possible future manipulations include a different baseline orientation (vertical instead of horizontal) and a different number of dots. Increasing the number of dots would allow to study other emergent features such as linearity and symmetry, thereby enabling us to uncover the potentially different processes underlying different emergent features.

CRediT authorship contribution statement

Celine Samaey: Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Johan Wagemans:** Conceptualization, Resources, Writing - review & editing, Supervision, Funding acquisition. **Pieter Moors:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Appendix A. Correlation matrices for response times and accuracies

Figs. A.1 and A.2.

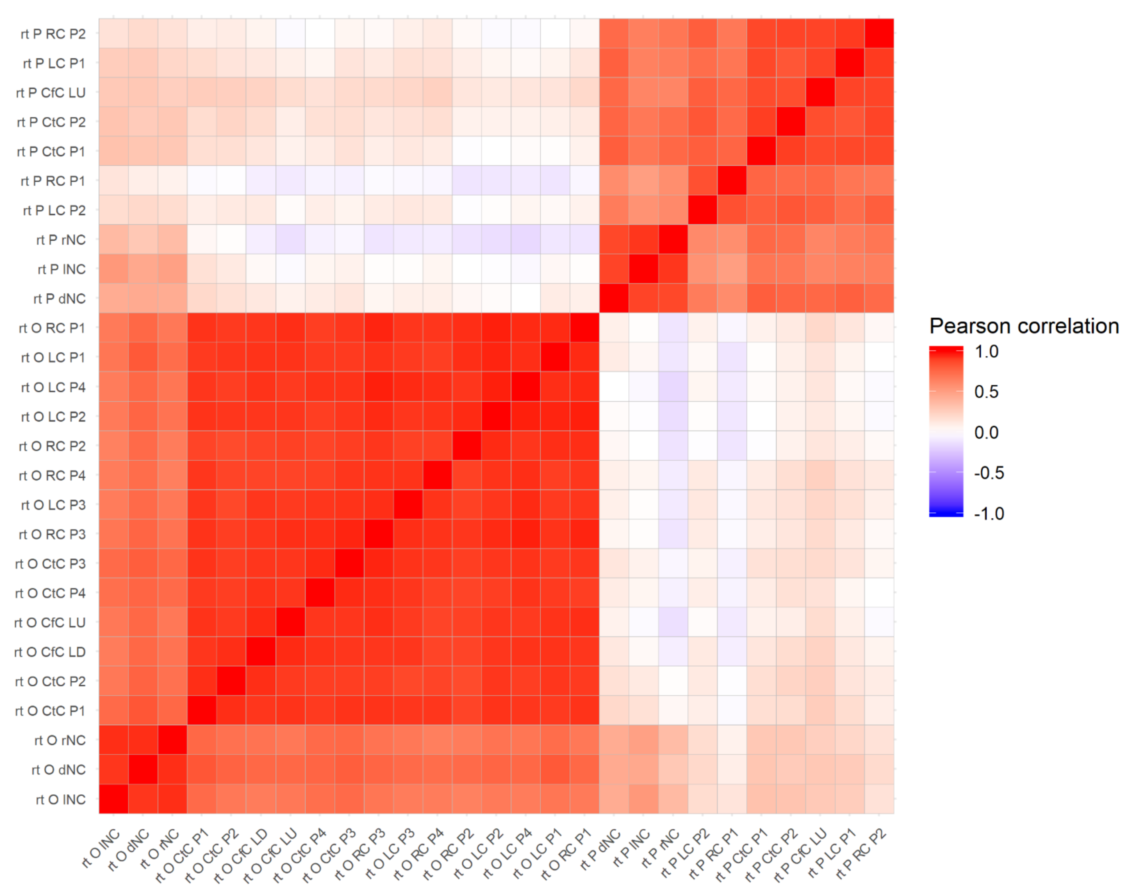

Fig. A.1. Correlation matrix for response times to all different stimuli. The description denotes the dependent variable, specific stimulus or condition as well as whether it was an orientation or proximity task. rt refers to response times. O and P refer to orientation and proximity. CfC (configural change), CtC (control change), dNC, lNC, rNC (double, left, and right no change), LC and RC (left and right change) refer to the specific type of change. LD and LU (left down and up) and P1 to P4 (position 1 to 4) refer to the specific change in position for a particular trial. The ordering of the variables was determined by hierarchical clustering using the complete linkage method, which aims to find similar clusters.

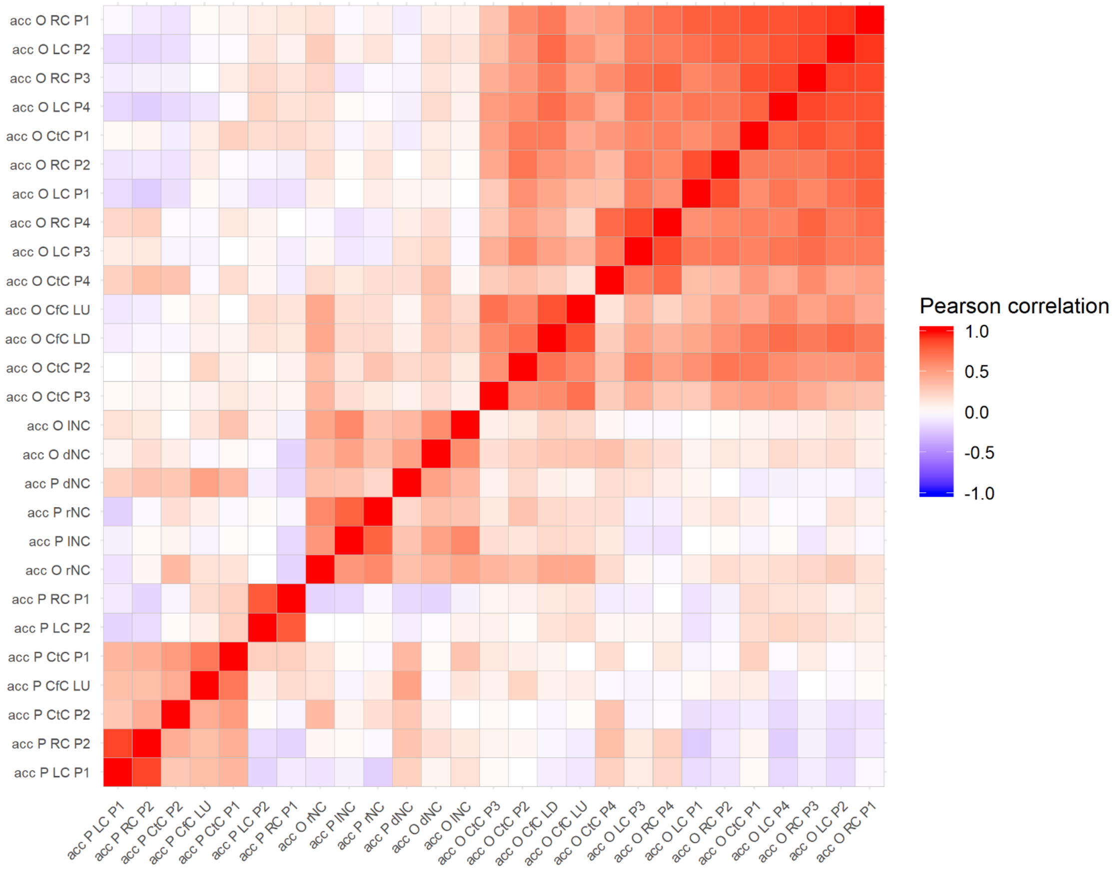

Fig. A.2. Correlation matrix for accuracies for all stimuli. The description denotes the dependent variable, specific stimulus or condition as well as whether it was an orientation or proximity task. acc refers to accuracy. O and P refer to orientation and proximity. CfC (configural change), CtC (control change), dNC, lNC, rNC (double, left, and right no change), LC and RC (left and right change) refer to the specific type of change. LD and LU (left down and up) and P1 to P4 (position 1 to 4) refer to the specific change in position for a particular trial. The ordering of the variables was determined by hierarchical clustering using the complete linkage method, which aims to find similar clusters.

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