Principal component analysis of behavioural individual differences suggests that particular aspects of visual working memory may relate to specific aspects of attention

Maro G. Machizawa a,b,* , Jon Driver a,b,c

a UCL Institute of Cognitive Neuroscience, University College London, United Kingdom
b UCL Institute of Neurology, University College London, United Kingdom
c Wellcome Trust Centre for Neuroimaging at UCL, University College London, United Kingdom

A R T I C L E   I N F O

Article history:
Received 16 November 2010
Accepted 22 November 2010
Available online xxx

Keywords:
Attention network
Visual working memory
Capacity
Filtering
Executive control
Individual differences

A B S T R A C T

The previously separate literatures on visual attention and on visual working memory are converging, with growing interest in how visual attention may relate to visual short-term memory, as exemplified by this special issue. We report exploratory analysis of how individual behavioural differences in separable aspects of attention may relate to particular aspects of visual working memory. Previous work with the Attention Network Test (ANT; Fan, McCandliss, Sommer, Raz, & Posner, 2002) proposed that it can measure three distinct aspects of attention: alerting, spatial orienting, plus executive control of response competition. We implemented the ANT in 50 healthy young adults, who also underwent a behavioural battery of visual working memory (WM) tests. These visual WM tests were all variations on recent paradigms, used here with the aim of measuring potential individual differences in visual WM capacity; WM precision; or WM distractor-filtering. Principal component analysis of the behavioural dataset revealed three main components. Interestingly, each component paired one aspect of ANT scores together with one aspect of WM scores, in terms of the strongest loadings. WM capacity loaded with ANT alerting; WM precision with ANT orienting; and WM filtering with ANT executive control. These results suggest that visual WM may involve separate component processes, and that different aspects of attention relate to different aspects of visual WM, in terms of behavioural individual differences. We discuss the observed pattern in relation to current issues and with respect to possible future work on the potential neural bases of individual differences in the distinct components.

* Corresponding author at: 17 Queen Square, Alexandra House, London WC1N 3AR, United Kingdom. Tel.: +44 0207 7679 1123; fax: +44 0207 7916 8517.
E-mail address: m.machizawa@ucl.ac.uk (M.G. Machizawa).

0028-3932/$ – see front matter © 2010 Elsevier Ltd. All rights reserved.

028-3932/S – see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.neuropsychologia.2010.11.032

Here we focus on visual WM in particular. It has frequently been suggested that WM capacity for simple visual stimuli such as oriented bars, colour patches or symbols might average around 3–4 items (e.g. Cowan, 2001; Luck & Vogel, 1997; Vogel & Machizawa, 2004). But this remains debated, with other suggestions being made. Visual WM might involve capacity being flexibly allocated, to fewer items with more precision, or to more items with less precision (e.g. Bays & Husain, 2008; see also Bays, Wu, & Husain, in this issue). It has also been proposed that apparent differences in WM capacity between individuals might primarily reflect their ability to prevent distractor stimuli from entering WM (e.g. McNab & Klingberg, 2008; Vogel, McCollough & Machizawa, 2005).

Recent work has sought not only to identify psychological subprocesses contributing to WM (e.g. see Baddeley, 1986, 2007; Engle, 2002), but also to relate these to brain regions and underlying neural mechanisms (e.g. McNab & Klingberg, 2008; Vogel et al., 2005; Xu & Chun, 2009). Space limitations here preclude a fully exhaustive review of this large and expanding field of research (see Jonides et al., 2008, for one overview, as well as the other articles in this issue). Instead we focus here on three recent developments that...
have sought to identify the basis for visual WM capacity limits; for WM precision; and for filtering of distractors from WM. These recent developments then lead into our own exploratory empirical study.

The number of items that can be successfully retained over a short delay, in a given visual WM task, typically hits an asymptote as set-size is increased. Characteristically different maxima are reached for different individuals (e.g. Cowan, 2001; Luck & Vogel, 1997; Vogel & Machizawa, 2004). This has led to the conception that each person has a characteristic visual WM capacity. Some authors have suggested that WM may have a corresponding limited number of ‘slots’ for retaining items (e.g. Luck & Vogel, 1997; Zhang & Luck, 2008), although other conceptions are possible (e.g. Bays & Husain, 2006; see also below). Recent studies using cognitive neuroscience methods sought to identify neural responses that vary with the set-size to be retained in visual WM, while reaching an asymptote when the subject’s performance does, against increasing target set-size. Vogel and colleagues (Vogel & Machizawa, 2004; Vogel et al., 2005) reported that a sustained posterior ERP component (so-called ‘CDA’, which reflects contralateral delay activity) covaried with target-set size in a visual change-detection WM task, asymptoting in a manner that correlated with individual differences in behavioural WM capacity. In separate but potentially related fMRI work, BOLD signals in parietal cortex were found to covary with visual WM target set-size, and to asymptote against set-size in a similar manner to performance (e.g. Todd & Marois, 2004; Xu & Chun, 2006, 2009).

In subsequent theoretical and behavioural work, Bays and Husain (2008, 2009) critiqued the notion of visual WM having a strictly limited capacity in terms of the number of items (or corresponding representational ‘slots’) that can be retained. They suggested instead that visual WM may constitute a ‘resource’ that can be flexibly allocated to more items with less precision for the information retained, or to fewer items with more precision in the retained information. The concept of variable WM precision is thus now a key emerging topic, although as yet relatively little is known about its possible neural basis.

A third key emerging issue in recent cognitive neuroscience work on visual WM concerns the ability to filter out distractors so that WM resources are allocated only to targets (e.g. McNab & Klingberg, 2008; Vogel et al., 2005). Vogel and colleagues measured EEG while manipulating whether or not subjects had to ignore distractors within the hemifield that was task-relevant for their visual WM task. Vogel et al. found that the posterior CDA component related systematically to individual differences in the ability to filter out such distractors. McNab and Klingberg used fMRI to study a paradigm where any requirement for distractor filtering could be pre-cued at the start of each trial. Their results implicated a frontal-basal ganglia/parietal network in anticipatory filtering, with frontal-basal ganglia interplay apparently controlling which items subsequently enter parietal storage, again in a manner that related to individual differences in the ability to overcome distraction.

More generally, efforts to understand individual differences in WM abilities may shed light not only on the nature of individual variation, but also on the underlying processes that contribute to WM (e.g. see Just & Carpenter, 1992; Luck & Vogel, 1997; McNab & Klingberg, 2008; Pashler, 1988; Todd & Marois, 2004; Underwood, 1975; Vogel & Awh, 2008; Vogel & Machizawa, 2004). Here we adopt a behavioural individual-differences approach to studying the possible relation of visual WM processes to visual attention processes, commensurate with the general theme of this special issue.

Although traditionally visual attention and visual WM were studied as separate topics, there is increasing interest in their possible inter-relation, and the previously separate literatures are coming together (e.g. Duncan & Owen, 2000; Lepsien, Griffin, Devlin, & Nobre, 2005; Postle, 2006; Vogel et al., 2005; see also the other articles in this special issue). Moreover the three current themes that we highlighted for current work on visual WM above (i.e. limited capacity, precision, and distractor filtering) resonate strongly with enduring themes in the selective attention literature, which has long been concerned with the putative limited capacity of attentional mechanisms (e.g. Bundesen, Habekost, & Kyllingsbaek, 2005; Driver, 2001; Duncan & Humphreys, 1989), with the possible impact of attention on the precision of visual processing (e.g. Driver, 2001; Spitzer, Desimone, & Morán, 1988; Yeshurun & Carrasco, 1998); and with the role of attention in distractor filtering (e.g. Driver, 2001; Lavie, 2005; Morán & Desimone, 1985). Here we took a behavioural individual-differences approach to study how different aspects of visual attention might relate to the three aspects of visual WM (capacity, precision, and filtering of distractors) that we briefly outlined above.

To measure behavioural individual differences in different aspects of visual attention, we used the well-established Attentional Network Test (ANT), as originally introduced by Fan, Posner and colleagues (Fan, McCandliss, Sommer, Raz, & Posner, 2002) for exactly that purpose. They proposed that the single ANT paradigm can provide individual measures of three separable aspects of attention, namely: alerting (in the form of benefits in performance due to a warning signal); spatial orienting (performance effects of a spatial cue); and executive control of conflict (in response to flanker distractors that can induce response competition), all within the same ANT paradigm. Much subsequent research has confirmed the utility of the ANT as an efficient paradigm for rapidly measuring these three putatively separate aspects of attention (e.g. Iba, Krompinger, & Baine, 2007; but see also Redick & Engle, 2006, for a critique). See Fig. 1 for an illustration of our implementation of the ANT paradigm, as administered here to 50 healthy adults.

We anticipated that the ANT measures would yield behavioural individual differences in alerting, spatial orienting, and executive aspects of attention, as in previous work with the ANT paradigm. Our new aim here was to explore how such individual differences in aspects of attention may relate to individual differences in aspect of visual WM, as assessed behaviourally here. We implemented a visual WM “battery”, comprising four somewhat different visual WM tasks, as illustrated in Fig. 2. These tasks were variations on recent studies that related to ongoing work on visual WM in our laboratory. For present purposes, the aim was to derive behavioural measures of visual WM capacity, precision, and distractor-filtering (i.e. for the three key aspects of visual WM briefly introduced above), from a short battery of visual WM tasks performed separately from the ANT task. We then sought to test for any underlying relations between individual differences in the three different aspects of visual WM, and the different aspects of attention as measured separately by the ANT. To explore any such relations, we submitted the behavioural data to standard principal components analysis (PCA) with rotation. PCA is a well-established, standard approach for reducing the dimensionality of a large dataset, in order to identify any structure in the relationships between variables that might otherwise be hidden. PCA will highlight those underlying components that explain the most variance in the dataset as a whole. As is well known, PCA can therefore identify relationships that might otherwise remain hidden, being potentially missed by other approaches such as pairwise correlations that only consider two aspects of the dataset at a time, rather than the full pattern.

Although PCA is an exploratory analysis technique, rather than a specific hypothesis-testing approach, we can nevertheless briefly outline a priori some of the possible outcomes in relation to extant hypotheses in the field. As regards visual WM, if as some have suggested (e.g. Bays & Husain, 2008) the ‘capacity’ and the ‘precision’ of visual WM are really two sides of the same coin (i.e. both potentially reflecting allocation of the same limited resource), then presumably individual differences in WM capacity and WM precision might
Fig. 1. Example trial sequences for different cue type in the ANT paradigm of Fan et al. (2002), as run here in 50 healthy adult participants who also underwent a visual working-memory battery. To convey the ongoing sequence of trials, and the different flanker conditions, the figure illustrates two successive trials for each cue condition (although the actual sequence of cue types was randomized in the experiment). This ANT paradigm has been proposed to assess at least three different aspects of attention (see main text, Section 1.5). There are four cueing conditions: no cue, double cue, centre cue, and spatial cue conditions, as defined by the event at trial onset (first and fifth panel in each row here). Cue(s) appeared at 1° above or below the central fixation cross for 100 ms. After 400 ms delay, a target arrow was presented above or below fixation (after a spatial cue, this was at the same location as the preceding cue) accompanied by two flankers on each side (four flankers in total; see third and seventh panel in each row here). There were three types of flankers: horizontal lines (neutral), arrows pointing in the same direction as the central target arrow (congruent), or arrows pointing in the opposite direction as the target (incongruent). All cue and flanker types were equiprobable in a random order. Participants were required to respond to the direction of the target arrow by corresponding left or right button press as quickly and accurately as possible.

There were three types of flankers: horizontal lines (neutral), arrows pointing in the same direction as the central target arrow (congruent), or arrows pointing in the opposite direction as the target (incongruent). All cue and flanker types were equiprobable in a random order. Participants were required to respond to the direction of the target arrow by corresponding left or right button press as quickly and accurately as possible.

The most novel aspect of our study is to examine how individual differences on the different WM scores potentially relate to individual differences on the separate ANT scores. PCA is the appropriate exploratory data-analysis approach for extracting any underlying components for individual differences within the full behavioural dataset, thereby allowing us to assess how the loadings for such components may relate between WM and ANT measures. We hypothesized that filtering of distractors in visual WM might relate to executive control of conflict in ANT, on the assumption that there may be considerable overlap between mechanisms responsible for dealing with distractors on-line (as in the ANT paradigm) and for keeping distractors from entry into WM (as in one of our WM tasks, see Fig. 2d). We also hypothesized that the precision of visual WM might relate to orienting of attention (see also Spitzer et al., 1988). We had no a priori hypotheses for the possible relation between ANT alerting and WM capacity, but the strength of the data-led PCA approach is that it can straightforwardly test for any such principal relations within a dataset.

### 1. Materials and methods

Fifty healthy young adults (19 males and 31 females; aged between 19 and 35 years with a mean age of 25.9 years) were recruited, with normal or corrected vision by self-report, and without colour-blindness as tested with Ishihara plates. Each participant gave informed consent before performing all five behavioural tasks, to which the order of each experiment (including the ANT) was counterbalanced across participants. Each experiment included a central fixation cross onsetsetting at the start of each trial. On-line eye-tracking (not reported in full here) indicated acceptable adherence to the instruction to hold fixation, although this was not critical for our purposes given the task designs (e.g., the distractors were intermingled on the same side as targets for the WM filtering measure in Experiment 4; see Fig. 2d).

#### 1.1. Experiment 1 (WM capacity)

To assess participants’ visual WM capacity in the manner of other recent influential studies, WM performance was tested for a varied number of task-relevant colour patches (2, 4, 6 or 8 items on each side, in bilateral displays with one hemifield task-relevant) in a colour change-detection paradigm that was adapted from Vogel and Machizawa (2004); see Fig. 2a. Our use of brief sample displays (100 ms) and eye-tracking served to minimize saccades to the task-relevant pre-cued hemifield. The initial sample display could either be identical to the subsequent probe display presented 900 ms later (on-no-change trials), or equiprobably one of the colour patches on the task-relevant side for that trial (left or right, as pre-cued at trial start) could change. Such colour-change was only possible on the pre-cued side. Accuracy was stressed rather than response speed. Participants were instructed to memorize as many items as possible. So arguably WM capacity was stressed, rather than WM precision for each item.

Each trial started (see Fig. 2a) with central arrow cues for 200 ms located above and below the fixation cross, indicating which hemifield would be task-relevant on that trial (left or right were equiprobable in a random order). After a short delay of 300–500 ms, a sample array was presented for 100 ms (with 2, 4, 6, or 8 square colour patches on each side, each .75°×.75°). After a delay of 900 ms, the probe array was presented for 2000 ms, and participants had to make a change/no-change response (change/no-change trials were equiprobable). The inset of Fig. 2e summarizes graphically how all display items were presented within 90°-of-polar-angle ‘sectors’, symmetrically located in each hemifield, as illustrated with the lighter shading in the inset of Fig. 2e. These same spatial sector parameters applied across all WM tasks here (Experiments 1–4). The thick line in Fig. 2e represents the distance (in degrees of visual angle) from central fixation to the most peripheral aspect of any stimulus display (10°); the dashed line represents the distance to the least peripheral (4°). Each item was pseudorandomly located within these sectors, with a minimum centre-to-centre separation of 1.5° from the nearest other item. Each item in Experiment 1 was pseudorandomly selected to have one of the seven highly discriminable colours (black, white, red, blue, yellow, green and violet) with no repetition within a hemifield, except that only one colour repetition per hemifield was allowed for
set-size 8 conditions. In other words, all seven colours were displayed, with one repeated at random, for sample displays at set-size 8 only. While this meant that the total number of repeated colours could in principle change (by one) for probe displays on change-trials at set-size 8, in fact performance did not differ between set-size 6 (where no colour repeats were possible) and set-size 8; see Section 2. Left and right attended conditions (as pre-cued on each trial, in random order) as well as change and no-change conditions were equiprobable in all set-size conditions. There was a total of 64 trials in each set-size condition (when disregarding which hemifield was relevant).

Only the higher set-sizes will challenge the capacity limits usually reported for such tasks (e.g. see Luck & Vogel, 1997; McHab & Klingberg, 2008; Vogel & Machizawa, 2004), with the lower set-sizes being at ceiling for most subjects as average capacity is typically around three to four items (Luck & Vogel, 2007). Accordingly, in order to capture individual differences we focused on $K$-estimates (Cowman, 2001; calculated here exactly as in Vogel & Machizawa) for set-sizes 6 and 8 here, averaged together, pooling over left and right hemifields.

1.2. Experiment 2 (WM precision-A)

With the aim of testing each individual’s visual WM ‘precision’, WM for the orientation of two bars (in one or other hemifield, pre-cued as in Experiment 1) was tested in a paradigm adapted from Bays and Husain (2008). Participants were now required to indicate the direction (clockwise or counter-clockwise) of a change in orientation for one or the other of the two target bars, between sample and probe, across the same delay as for Experiment 1. The probe in Experiment 2 now contained only a single target (see Fig. 2b) and its orientation always changed with respect to the preceding sample, the question now being whether this was a clockwise or anticlockwise change (equiprobable). Accuracy was again stressed rather than speed. Participants were now instructed to memorize each target as precisely as possible. So ‘quality’ of WM was stressed, rather than quantity as in Experiment 1.

Cue displays and all timing and location parameters were identical to Experiment 1, only one of the two targets now appeared in the probe and just its orientation relative to the same item in the sample was varied (15, 30, 45 or 60° different, but given our specific interest in WM precision we focused only on the hardest 15° condition here, see below). Only two items were shown within each hemifield in the sample, which should be well within the putative typical WM capacity of three to four items (Luck & Vogel, 1997). There was a total of 64 trials in each sub-condition when pooling over left- and right-hemifield conditions.

As a WM precision measure, accuracy score on the most difficult (15° change in orientation) condition was chosen a priori, then multiplied by two (given that here two targets had to be retained but only one was probed), in order to make the score analogous to $K$-estimates (being a proportional score with respect to the number of items presented) and comparable to the scores acquired in Experiment 3 (see below), so the values obtained in Experiments 2 and 3 could be averaged together. We note in passing that if the data were re-scored in terms of a P-estimate (analogous to the estimate of WM precision used by Bays and Husain, 2008), this correlated very strongly with the $K$-estimates we used, both for Experiment 2 alone ($r(49) = .83; p < .001$) as well as when our precision measures from Experiments 2 and 3 (see below) were pooled ($r(49) = .76; p < .001$).

1.3. Experiment 3 (WM precision-B)

Due to other ongoing research in our laboratory, we also ran a separate second measure of visual WM precision. This was similar to the change-detection task of Experiment 1, but used lower set-sizes and oriented bars (see Fig. 2c) as in Experiment 2, rather than coloured patches as in Experiment 1. The initial sample displays towards the start of each trial were identical to Experiment 2 (compare Fig. 2b and c). Analogous to Experiment 1, each probe display at trial end now always contained the same number of items as the preceding sample display, and one of these items could change (now only in orientation) in the pre-cued relevant hemifield between sample and probe. As in Experiment 2, the orientation change could be 15° or larger, but again we focused (see below) on just the smallest 15° changes to provide a sensitive measure of visual WM ‘precision’ for those trials that required the most precision. We measured performance in this change-detection version of...
the experiment (as in many other visual WM studies; e.g. McNab & Klingberg, 2008; Todd & Marois, 2004; Vogel & Machizawa, 2004; Xu & Chun, 2006) by calculating the conventional K-estimate defined as \((H - F) / 2\), where \(H\) refers to hit-rate, and \(F\) refers to false-alarm-rate, with the outcome then being doubled here to the set-size of two targets on the cued side. As it turned out, individual differences in the precision-A measures of Experiment 2 correlated quite strongly with those for the precision-B measures of Experiment 3 \((r(49)= .52; p < .001)\). Moreover, the PCA results obtained actually turned out to be nearly identical (i.e. retaining similarly high components and similar loadings) regardless of whether we focus on just Experiment 2 or just Experiment 3 (or instead combine these) for our measure of individual variation in visual WM precision. Accordingly, the summary PCA results presented here, we averaged over Experiments 2 and 3 (for the most ‘precise’ 15 orientation-change conditions) to yield a single WM precision measure for each individual participant in the dataset that underwent PCA.

1.4. Experiment 4 (WM filtering)

To examine each individual’s ability to filter out irrelevant distractors while retaining targets, we used another orientation-change detection paradigm (see Fig. 2d), adapted from the first experiment in Vogel et al. (2005). This now included spatially intermingled distractor bars in a different colour that participants had to ignore. Target and distractor colours were counterbalanced across participants, such that the roles of red and green were reversed every two successive participants. In particular, the instruction was provided to each participant at the start only that targets would appear on the relevant pre-cued side in one particular colour, and to ignore the intermingled bars in the other colour (with the colour roles constant throughout the experiment for any individual participant). Any orientation change was now large (45°) so that we did not tax WM precision (cf. Experiments 2 and 3 above), and all participants were tested with pre-cued targets only. To rule out any confounding effects from differences in temporal and spatial frequencies, the targets and distractors were presented in a random interleaved order with a unique orientation, and occasionally replaced by distractor bars in the other colour (cf. Vogel et al., 2005) within each hemifield (see Fig. 2d for an example of the latter condition, with two stimuli in the target colour and two in the distractor colour on each side). The critical measure of distractor filtering corresponded to how well performance was preserved (in terms of K-values) for the condition with distractors present relative to the condition with no distractors present. The filtering efficiency was calculated as the K-value for the two targets with distractors condition, divided by that of the two targets without distractor condition.

1.5. Experiment 5 (attention network TASK)

The ANT paradigm (see Fan, Flombaum, McCandliss, Thomas, & Posner, 2003; Fan et al., 2002) comprises 12 distinct conditions within a single paradigm (see Fig. 1 here for schematic illustrations) that are then used to elucidate 3 putatively separate aspects of attention: alerting, orienting, and executive control of conflict. The task is to judge whether target arrows, appearing above or below fixation, point left or right to the subsequent target, and are therefore compatible or incompatible (see Fig. 1: leftmost panels) there are 4 cue conditions (no-cue, double-cue, centre-cue, and valid peripheral spatial-cue conditions); as well as 3 flanker conditions, see third and seventh panels from left in all the example sequences of Fig. 1. The flankers can either be neutral (corresponding to horizontal bars), or incongruent (arrow flankers pointing in the same direction as the target); or incongruent (arrow flankers pointing in the opposite direction to the target arrow). Participants were instructed to respond to the direction of the target arrow in the middle by pressing a corresponding button, while ignoring any flankers.

Unlike our four WM tasks that all stressed accuracy/speed of response as well as accuracy was stressed in the instructions for the ANT task (see also Fan, Flombaum, et al., 2003; Fan et al., 2002). Since speed and accuracy can trade-off (Pew, 1969) so that consideration of both reaction time and accuracy is essential (Fan & Posner, 2004), we combined reaction time and accuracy measures together when calculating our ANT scores for each condition here. Specifically we calculated ‘efficiency’ as proportion correct divided by RT (see Davis, Driver, Pavani, & Shepherd, 2003, for another example of such a measure, plus many further papers). We made this particular division (rather than vice-versa) in order to yield higher scores for better performance, which is then directionally analogous to the accuracy scores and K-value estimates used for all our WM scores. While the absolute scores will inevitably differ across our WM and ANT paradigms due to estimation of K-values for WM, versus division by RT only for the ANT, please note that it is the relative differences between particular conditions that matter here, and individual variation in these across tasks. Please note also that all our decisions about the particular measures to utilize from each experiment for the dataset that underwent PCA were made a priori, without regard to the subsequent outcome, and thus, likely to be an unbiased assessment of between-task variation.

As in Fan et al. (2002) and Fan, Flombaum, et al. (2003), neither the no-cue nor double cue conditions indicate the spatial location of the upcoming target, but the double cues provide temporal warning of imminent target onset. Hence benefits due to the double cue over no cue are attributed (by Fan and colleagues) to alerting. Analogously, differences between the central and the peripheral spatial cues are attributed to spatial orienting. Finally differences between congruent and incongruent conditions are attributed to executive control of conflict. In these respects our interpretation of our efficiency-based ANT scores matches with Fan and Posner (2004).

1.6. Principal component analysis (PCA)

As mentioned earlier, PCA is a well-established analysis technique for highlighting hidden relations that explain the most variance in a dataset as a whole. Accordingly, the six types of score described above (corresponding to our estimates of WM capacity, WM precision, WM filtering, ANT alerting, ANT orienting, and ANT executive for each participant) were subjected to PCA for our dataset from 50 participants. One issue with PCA concerns how many components to retain. The convention of setting the cutoff for retained eigenvalues at 1 has been criticized as too arbitrary (see Horn, 1965; O’Connor, 2000). Accordingly, here we followed the well-established ‘parallel analysis’ procedure that has been shown to provide a more robust, statistically valid approach for resolving the number of components to retain from a PCA (Horn, 1965; O’Connor, 2000). Parallel analysis computes 95% confidence intervals for each associated eigenvalue, via a Monte-Carlo simulation based on random, uncorrelated variables. In order to determine the eigenvalue thresholds for resolving which successive components to retain from the PCA (in our case, six possible eigenvalue thresholds given our analysis of six variables), we implemented parallel analysis to yield 95% confidence interval thresholds (O’Connor, 2000) for 50 samples with 6 variables prior to the PCA on our experimental data. The actual PCA on our experimental data then used the eigenvalue thresholds as pre-set by the parallel analysis. As it turned out, three significant components were retained as above the eigenvalue thresholds derived from parallel analysis. In fact all three retained components’ eigenvalues were above one, and all further components below one, so that the convention of thresholding eigenvalues at one, without parallel analysis, would have yielded identical results to our own approach utilizing parallel analysis. Please note also that the parallel-analysis approach allowed this issue of how many components to retain from the PCA to be resolved in an unbiased way, with regard to whether the underlying scores loading on particular components retained complete/ANT scores. Thus the full data pattern determined the underlying components, rather than any prior theoretical biases.

The retained components were then Varimax rotated (Wood, Tatarayan, & Gorsuch, 1996), in accord with the standard PCA approach. See Garrido et al. (2009), for a recent example of applying an analogous PCA approach – except without the reliance on parallel-analysis eigenvalue thresholds – to individual differences in behavioural scores as here (albeit for the very different topic of face recognition in their case).

2. Results

We first report brief summary results for each WM experiment plus the ANT test, before going on to focus on the specific measures that underwent PCA analysis and the outcome of that. These summary results for each experiment are not critical for our purposes, but serve as a ‘reality check’ before proceeding to the new concerns in our exploratory PCA analysis of how the different measures may relate. All of the summary results from each experiment turned out as would be expected given prior research (e.g. worse WM performance for higher set-sizes; a tendency for worse WM performance in the presence of intermingled distractors; and better performance with congruent than incongruent flankers in the ANT task, or with appropriate pre-cuing in that task).

2.1. WM task overall results

The mean proportion correct (with standard deviation) in each WM task was as follows (see Fig. 3). For set-sizes 2, 4, 6 and 8 in Experiment 1 the mean proportions correct were .93 ± .05; .80 ± .05; .68 ± .09; and .65 ± .08, respectively. Mean K-values (again with standard deviations) for set-sizes 2, 4, 6 and 8 were \(1.72 ± 0.20; 2.37 ± 0.72; 2.13 ± 0.06\) and 2.34 ± 1.36, respectively. As expected, set-sizes 6 and 8 showed larger variation between individuals than the other two smaller set-size conditions that should be within typical WM capacity, in accord with Luck and Vogel (1997) and Vogel and Machizawa (2004).

Proportion correct (with standard deviation) for the 15°; 30°; 45° and 60° rotation conditions at set-size 2 in Experiment 2 were \(72.70 ± 0.10\); \(80 ± 0.10\); \(78 ± 0.10\); and 71 ± 0.10, respectively. The corre-
sponding values in Experiment 3 were \(0.66 \pm 0.07, 0.82 \pm 0.08, 0.88 \pm 0.08\), and \(0.90 \pm 0.08\), respectively. The mean derived K-estimates (with standard deviation) for these conditions were \(0.89 \pm 0.42, 1.19 \pm 0.42, 1.12 \pm 0.39, 0.83 \pm 0.40\), respectively in Experiment 2; and K-estimates were \(0.61 \pm 0.29, 1.28 \pm 0.32, 1.52 \pm 0.33\); and \(1.58 \pm 0.31\), respectively in Experiment 3. As would be expected (e.g. see Bays & Husain, 2008), smaller changes in orientation led to worse performance in both Experiments 2 and 3, with the 15° condition (on which we focused for our precision-measures) being the hardest as expected. The results for the 60° condition (which, along with 30° and 45°, we did not consider further) may seem somewhat anomalous within Experiment 2, but with the benefit of hindsight this is merely due to increased ambiguity about which end of the bar was which - and hence in which direction it had rotated, as had to be judged in Experiment 2 only - for the 60° condition. Note that as the rotation increases towards 90°, it becomes impossible to judge the direction of rotation, due to ambiguity over which end of the bar is the ‘head’ and which is the ‘tail’. This issue for the largest (60°) rotation we used arose more for the Experiment 2 than Experiment 3, as in the latter participants did not need to judge rotation-direction (just change or no-change). But since the precision scores that we submitted to PCA only concerned the hardest (thus requiring most precision) 15° conditions from Experiments 2 and 3, the anomaly for 60° in Experiment 2 is immaterial for our purposes.

In Experiment 4, mean proportion correct (with standard deviation) was \(0.90 \pm 0.08\) for set-size 2 without distractors; \(0.86 \pm 0.09\) for set-size 2 with 2 distractors; and \(0.72 \pm 0.09\) for set-size 4 without distractors. The corresponding derived K-values were \(1.59 \pm 0.31, 1.42 \pm 0.36\); and \(1.73 \pm 0.69\), respectively; see Fig. 3.

2.2. The three WM scores submitted to PCA (along with ANT scores as explained later)

From Experiment 1, the group mean and standard deviation of WM capacity estimates (K-values) averaged over set-size 6 and 8 was \(2.23 \pm 1.09\). For the estimates of working memory precision (averaged over Experiments 2 and 3 in the hardest 15° orientation-change conditions, as explained above), the group mean K-values was \(0.76 \pm 0.31\) (note the relatively low score, due to the small orientation change). For distractor filtering in Experiment 4, the group mean filtering efficiency score was \(0.90 \pm 0.17\) (where 1 would indicate perfect filtering; i.e. same performance with two targets plus two distractors on each side, as for only two targets with no distractors). We provide these summary group means for information, but please note that the corresponding scores for each individual \((N = 50)\) provided the data that underwent PCA. As explained earlier, PCA is a more effective means for identifying any otherwise hidden patterns in the full dataset than mere pairwise correlations, since the latter do not consider the full dataset. Nevertheless, for completeness we note that only relatively weak tendencies for correlations were found between our different WM scores here across individuals (specifically, \(r(49) = .22, p = .06\) one-tailed, between WM capacity and filtering scores; \(r(49) = .24, p = .04\) one-tailed, between
capacity and WM precision; no other significant correlations found between WM measures).

2.3. Attentional Network Test overall results

Fig. 4 shows mean efficiency scores (which combine RT and accuracy into one composite score as explained earlier) averaged across all 50 participants for each condition. Prior to the PCA on the three selected ANT scores plus three WM scores, the ANT efficiency scores in each condition were analysed for completeness. A repeated-measure ANOVA, with Greenhouse-Geisser correction when required (corrected degrees of freedom listed when so) revealed significant effects of cue type (F(2,57,125.90) = 76.32; p < .001) and flanker type (F(1,12,54.93) = 289.09; p < .001), plus an interaction between these two (F(6,294) = 11.30; p < .001, for which no correction was needed). Bonferroni corrected pairwise t-tests indicated that incongruent flankers led as expected to less efficient performance (mean efficiency, E, of 1.46) than the neutral (E = 1.94) or congruent (E = 1.94) conditions, at p < .001 for both comparisons; see Fig. 4. In accord with Fan et al. (2002), neutral and congruent conditions did not differ in our sample. Indeed, a further repeated-measure ANOVA including only the neutral and congruent conditions found no significant term due to congruent versus neutral (all p > .82). To accord with recent ANT research that has focused on just the congruent and incongruent flanker conditions (see Fan, Fossella, Sommer, Wu, & Posner, 2003; Fan, McCandliss, Fossella, Flombaum, & Posner, 2005), we accordingly excluded the neutral flankers for the dataset that underwent PCA.

As regards cueing effects, the no-cue condition yielded the worst performance, and the spatial cue was the best overall (centre and double-cue conditions did not differ here, but the other pairings all did overall, at p < .001); see Fig. 4. Finally, the interaction arose due to the somewhat different cueing pattern in the incongruent conditions (see rightmost four data-points in Fig. 4) compared to the congruent (or neutral) conditions (see central four data-points, or leftmost four data-points, in Fig. 4). Specifically, the double-cue conditions differed from the no-cue conditions with congruent or neutral flankers (each at p < .001), but not with incongruent flankers (see Fig. 4).

2.4. The three ANT scores submitted to PCA (along with three WM scores)

Since the usual ‘alerting’ benefit of double-cue versus no-cue conditions (cf. Fan et al., 2002) was absent here for the specific context of incongruent flankers (see Fig. 4), we henceforth calculated that alerting benefit for the congruent condition instead in each participant. Note once again that this decision was taken prior to the implementation of PCA. Following Fan et al. (2002), the ‘orienting’ score was calculated as the difference between the spatial cue condition versus the no-cue condition, pooling across both congruent and incongruent flanker congruency. Finally, the putatively executive-function-related “conflict” score was calculated as the difference between congruent and incongruent conditions. As mentioned previously (Section 1.5), here we calculated all of these putatively separate aspects of attention using the efficiency scores, since these combine both accuracy and RT.

In summary, each ANT difference-score based on the efficiency results was calculated and interpreted similarly to Fan and Posner (2004), as follows for each participant. Alerting efficiency was estimated via the double-cue condition minus no-cue condition for congruent flankers (more efficiency for double-cue than no-cue trials was considered to indicate an alerting benefit from the double-cue, and/or, some difficulty in maintaining alertness without a cue). Orienting efficiency was estimated via the spatial cue condition minus the centre cue across both congruent and incongruent flanker conditions (more efficiency with spatial-cues than centre-cues indicates beneficial orienting to the spatial cue and/or potential disengagement difficulties from the centre cue). Executive efficiency was estimated via the congruent flanker conditions minus the incongruent conditions, regardless of cueing (such response competition effects are considered to index executive function by Fan & Posner, 2004, among others).

From the ANT measures recorded in Experiment 5 (with neutral flankers now excluded since not differing from congruent, as noted above; see also Fan, Fossella, et al., 2003; Fan et al., 2005; Fan & Posner, 2004), the group mean (plus standard deviation) beneficial change in efficiency scores due to alerting averaged .18 ± .12; for spatial orienting the average effect was .09 ± .11; and for executive control the average effect of response congruency/incongruency was .48 ± .21, with all of these scores being defined by analogous comparisons of conditions as in Fan, Fossella, et al. and Fan et al. But please note that it was the scores for each individual (N = 50) that underwent PCA, on the three ANT measures and three WM measures that we have described. In accord with previous research using the ANT, here we found that the three different ANT measures did not correlate with each other (p > .17 for all such pairwise correlations).

2.5. PCA results

Table 1

Table 1 Loadings on each of the three principal components retained from the PCA, as determined by thresholds from the parallel analysis, shown after Varimax rotation. Note that each of the three principal components obtained tended to load strongly on one WM measure and one ANT measure (see bolded pairs of figures in table). Note also the negative value of the loading for ANT orienting on the second component, along with a positive value of this loading for WM precision.

Based on the parallel analysis for 50 samples with 6 variables, eigenvalue thresholds (95% upper confidence limit of the distribution of eigenvalues derived from the random data in the parallel analysis) for retaining each successive component from a maximum of six successive components were: 1.49, 1.24, 1.05, .90, .74, and .57. The actual resulting eigenvalues for successive components from the PCA on our dataset (with 3 ANT scores and 3 WM scores per participant, see above) were 1.50, 1.29, 1.12, .87, .75, and .47. Accordingly just the first three principal components were retained as above the threshold determined by the parallel analysis, and were then subjected to Varimax rotation. As noted earlier, the parallel analysis provides a well-established formal means for identifying the number of components that should be retained from the PCA, in a manner that is completely unbiased with respect to our current concerns. For instance, nothing about the parallel-analysis (or the PCA) enforces that particular WM scores should load artificially with particular ANT scores, rather than (say) one WM score with another.

But remarkably, each of the three principal components obtained turned out to load most strongly on one WM measure and one ANT measure. As shown by the bolded values in Table 1, the first component loaded not only with our measure of WM capacity but also with ANT-derived alerting; the second component loaded not only with WM precision but also with ANT-derived
orienting; while the third component loaded not only with WM filtering but also with ANT-derived executive function (in relation to congruency/incongruency effects). The first principal component explained 25% of the variance; the second 22%; and the third 19%. So cumulatively these three components (each of which turned out to pair one WM score with one ANT score, in terms of their loading; see Table 1) accounted for 66% of the variance in observed behavioural individual differences.

3. General discussion

In 50 healthy adult participants we collected behavioural scores from four visual WM tasks, adapted from recent paradigms with the aim of assessing potentially dissociable components of visual WM (namely WM capacity, WM precision, and WM filtering). We also collected data on the same 50 participants for the ANT task of Fan et al. (2002) and Fan, Flombaum, et al. (2003), that was introduced by them with the aim of measuring three different components of attention (alerting, orienting, and executive-control of conflict) within a single task. A standard principal components analysis (PCA) was pre-cued in our WM tasks that sought to measure visual WM precision (see Fig. 2b and c), the exact location of the target stimuli within the sizeable spatial sector where stimuli could appear (see Fig. 2e) within each hemifield was not. Hence exact target locations varied randomly from trial to trial here, meaning that individual differences in the covert spatial orienting to these exact locations might potentially arise.

3.3. Orienting and WM precision

The remaining significant component to emerge from PCA (henceforth labelled ‘quality’, for ease of exposition) loaded on both the WM precision measure and the ANT orienting measure. It should be noted that this reflected a negative relationship between the two as indicated by the loadings (see Table 1), so that better precision scores tended to go along with smaller spatial pre-cuing effects in the ANT task. This might reflect better exogenous spatial orienting to un-cued stimuli in subjects with higher WM precision. Speculatively, this could potentially relate to Bays and Husain’s (2008) work on visual WM precision, if one assumes that higher precision follows from more efficient allocation of attention to stimuli when they appear at locations that have not been pre-cued, as in the Bays and Husain WM paradigm, and as for the un-cued condition in the ANT task here. Bays and Husain found better precision at a (presumably attended) saccade-target location. Although we discouraged rather than encouraged saccades, we suggest that individual differences in the ‘quality’ component might potentially reflect differences in spatial orienting. Please note that although the task–relevant hemifield was pre-cued in our WM tasks that sought to measure visual WM precision (see Fig. 2b and c), the exact location of the target stimuli within the sizeable spatial sector where stimuli could appear (see Fig. 2e) within each hemifield was not. Hence exact target locations varied randomly from trial to trial here, meaning that individual differences in the covert spatial orienting to these exact locations might potentially arise.

3.4. Future directions

Taken together, the principal components that we found via standard PCA uncovered relations in behavioural individual differences between, on the one hand, WM measures from tasks requiring comparison across a 900 ms delay period; and, on the other hand, behavioural ANT measures from an on-line task without any delay period. This provides a new type of evidence that separable processes contributing to attention may also contribute to different aspects of WM performance. In principle we could have found that all of the WM measures (or some of them) loaded more strongly with each other than with the separate ANT measures for aspects of attention. But instead, we found that each aspect of attention as assessed by the ANT tended to load with a specific aspect of WM as assessed by the separate WM battery (see Table 1). Previous work with the ANT had already indicated the separability of different aspects of attention. Recent work on visual WM (see Introduction) has begun to identify potentially separable processes underlying WM performance. Now our new data suggest that particular aspects of visual attention may relate, in terms of individual differences, to particular aspects of visual WM.

Having identified these principal components that apparently relate particular attentional processes to particular WM processes, future work could investigate the possible brain bases of such relations in individual-difference patterns. This could be approached both in terms of variation in brain structure (e.g. Ashburner & Friston, 2000; Hutton, De Vita, Ashburner, Deichmann, & Turner, 2008; also see the recent relation of behavioural PCA components to voxel-based morphometry, by Garrido et al., 2009); and also for variation in brain function as assessed with fMRI, EEG or MEG. Applying the individual-differences approach to brain structure and function, in relation to behavioural principal components (cf. Garrido et al.), may shed further light on how different aspects of visual WM relate to specific aspects of visual attention. We are already conducting such research with the sample of partici-
pants reported here, applying brain measures and seeking to relate these to the initial behavioural components that we have uncovered.

4. Conclusions

Our results indicate, via behavioural individual differences, that separable aspects of visual attention may relate to specific aspects of visual working memory. Standard principal component analysis of the behavioural scores indicated one component (that we term ‘quantity’) for which visual WM capacity loaded together with ANT alerting; another (‘quality’) for which visual WM precision loaded together with ANT orienting; and a third (‘executive’) for which WM distractor filtering loaded together with ANT executive control of conflict. This pattern of components for behavioural individual differences may inform future studies of their neural basis, and of overlap versus dissociations between the underlying mechanisms. More generally, our results indicate that different measures of visual WM may tap into different underlying processes, including important roles for attentional functions.

Acknowledgements

This research was supported by the Wellcome Trust (programme grant to JD, plus core funding of the Wellcome Centre for Neuroimaging); and by a UCL Graduate School award to MM. JD is a Royal Society Anniversary Research Professor.

References


