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Thresholds for sine-wave corrugations defined by binocular disparity in random dot stereograms: Factor analysis of individual differences reveals two stereoscopic mechanisms tuned for spatial frequency

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ABSTRACT

Threshold functions for sinusoidal depth corrugations typically reach their minimum (highest sensitivity) at spatial frequencies of 0.2–0.4 cycles/degree (cpd), with lower thresholds for horizontal than vertical corrugations at low spatial frequencies. To elucidate spatial frequency and orientation tuning of stereoscopic mechanisms, we measured the disparity sensitivity functions, and used factor analytic techniques to estimate the existence of independent underlying stereo channels. The data set (N = 30 individuals) was for horizontal and vertical corrugations of spatial frequencies ranging from 0.1 to 1.6 cpd. A principal component analysis of disparity sensitivities (log-arcsec) revealed that two significant factors accounted for 70% of the variability. Following Varimax rotation to approximate “simple structure”, one factor clearly loaded onto low spatial frequencies (≤0.4 cpd), and a second was tuned to higher spatial frequencies (≥0.8 cpd). Each factor had nearly identical tuning (loadings) for horizontal and vertical patterns. The finding of separate factors for low and high spatial frequencies is consistent with previous studies. The failure to find separate factors for horizontal and vertical corrugations is somewhat surprising because the neuronal mechanisms are believed to be different. Following an oblique rotation (Direct Oblimin), the two factors correlated significantly, suggesting some interdependence rather than full independence between the two factors.

1. Introduction

Stereo vision allows us to judge depth from small binocular disparities between the images projected into both eyes. Given that our eyes are offset horizontally in the head, depth perception is based mainly on horizontal disparities. The use of random-dot stereograms (Julesz, 1960, 1971) enables us to present stimuli where the horizontal disparities between eyes is the sole cue to depth. In this way, one can construct the stereoscopic analogue of sinusoidal luminance gratings: corrugations showing sinusoidal depth modulations defined purely by horizontal disparity (Tyler, 1974; Tyler & Raibert, 1975).

1.1. Disparity sensitivity functions (DSFs)

Thresholds for sinusoidal corrugations defined by disparity differ as a function of modulation spatial frequency. The minimum thresholds (highest sensitivity) usually occur at spatial frequencies of 0.2–0.4 cycles/degree (cpd), with sensitivity decreasing markedly above or below the peak. This finding of this representative function was initially established for horizontal corrugations (Tyler, 1974; Rogers & Graham, 1982; Howard & Rogers, 2012).

In later studies adding vertical corrugations, DSFs have been shown to have a similar representative band-pass shape, but have shown a puzzling anisotropy. Corrugations showing sinusoidal modulations of horizontal disparities at low spatial frequencies are much easier to detect when they are horizontally oriented than when they are vertically oriented (Bradshaw & Rogers, 1999; Bradshaw, Hibbard, Parton, Rose, & Langley, 2006; Serrano-Pedraza & Read, 2010; Serrano-Pedraza, Brash, & Read, 2013; Serrano-Pedraza et al., 2016). The same anisotropy also applies to slanted surfaces rotated around the horizontal axis and rotated around the vertical axis (Mitchison & McKee, 1990; Gillam & Ryan, 1992; Cagenello & Rogers, 1993; Hibbard, Bradshaw, Langley, & Rogers, 2002). Recently, Serrano-Pedraza et al. (2016) have shown that the strength of the anisotropy increases with age during development, suggesting a role of visual experience in this anisotropy.

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1.2. Mechanisms underlying DSFs tuned to spatial frequency and orientation

Marr and Poggio (1979) initially presented a model including stereoscopic disparity channels. They suggested that (1) there is a range of channels with different levels of resolution establishing correspondence between stereo images (see also Tyler, 1973; Richards & Kaye, 1974). They further suggested (2) that the low-frequency channels precede and provide the foundation for higher frequency channels. Although the details are disputed, the basic idea of different channels has wide-ranging support (Mallot, Gillner, & Arndt, 2004; Farell, Li, & McKee, 2004; Menz & Freeman, 2002).

The representative shape of the DSF has often been interpreted as evidence of multiple mechanisms, “channels”, or “high-level mechanisms” underlying the DSF. The low spatial frequency decrease in sensitivity has been explained in terms of multiple spatially-tuned disparity mechanisms, which interact through receptive fields’ lateral inhibition (Tyler & Julesz, 1978; Schumér & Ganz, 1979; Tyler, 1990). Additionally, to many, the stereo anisotropy implies that distinct neuronal mechanisms are involved in detecting slant about the horizontal and vertical axes. These are regarded as distinct channels.

Classic studies have demonstrated that for horizontally-oriented corrugations, selective tuning also exists for different spatial frequencies (Cobo-Lewis & Yeh, 1994; Tyler, 1983, 1975; Schumér & Ganz, 1979; Tyler & Julesz, 1978). Considerable evidence exists to suggest that there are two or three of such channels, with a bandwidth of around 3 octaves (Serrano-Pedraza & Read, 2010; Tyler, 1990). Until recently no one had examined the mechanisms underlying perception of vertical disparity corrugations, and indeed Serrano-Pedraza and Read (2010) had suggested from circumstantial evidence that there might only be a single channel tuned to vertical. However, more recent evidence has made it clear that both vertical and horizontal stereo corrugations are detected by multiple disparity channels. Serrano-Pedraza et al. (2013), using a critical-band masking paradigm with random dot patterns, concluded there are at least two channels for vertical corrugations, while Witz and Hess (2013), using a detection/discrimination paradigm with spatially band-pass noise, concluded that there are at least three.

1.3. Using individual differences to examine underlying mechanisms

In the present study, we use an alternative method to estimate the minimum number and the nature of mechanisms underlying DSFs. Here, we measure the disparity thresholds of 30 individuals for horizontally- and vertically-oriented depth corrugations of different spatial frequencies depicted in random-dot stereograms (Experiment 1). We compare these with similar thresholds for horizontal and vertical step-edges, which contain many different spatial frequencies (Experiment 2). To estimate the minimum number of and the nature of the mechanisms underlying DSFs, we analyze individual differences in our data using factor analytic techniques.

The essential general assumptions are: (1) individual differences in visual data are determined in part by individual differences in the mechanisms underlying those data, and (2) one can often use correlational and factor-analytic methods to infer the minimum number and nature of the mechanisms underlying those data (Peterzell, 1993; Peterzell & Teller, 2000; Wilmer, 2008; de-Wit & Wagemans, 2016; Peterzell, 2016). The methods for estimating spatiotemporal mechanisms from individual differences have been described elsewhere in a series of studies on contrast sensitivity (Peterzell, 2016; Peterzell, Werner, & Kaplan, 1991, 1993, 1995; Peterzell & Teller, 1996; Peterzell, Dougherty, & Mayer, 1997; Peterzell & Kelly, 1997; Peterzell, Chang, & Teller, 2000; Peterzell, Schefrin, Tragear, & Werner, 2000).

Several previous investigators have examined individual differences in data to elucidate stereoscopic and other binocular mechanisms (Barendregt, Dumoulin, & Rokers, 2016; Bosten et al., 2015; Chen, Maloney, & Clifford, 2014; Chopin, Levi, Knill, & Bavelier, 2016; Harker, 1982; Hibbard et al., 2002; Harris, Chopin, Zeiner, & Hibbard, 2012; Hildreth & Royden, 2011; Ling, Nefs, Brinkman, Qu, & Heynderickx, 2013; Meredith, 1965; Nefs, O’Hare, & Harris, 2010; Richards, 1970, 1971, 1977; Richards & Lieberman, 1985; van Ee, 2003; Tibdury, Black, & O’Connor, 2015; Wilmer, 2008; Wilmer & Backus, 2007, 2008; Wismeijer, Erkelen, van Ee, & Wexler, 2010). Hibbard et al. (2002) for instance, used individual differences in the stereoscopic anisotropy to provide evidence that sensitivity to surface tilt and slant is in part limited by the sensitivity to luminance-defined orientation and spatial frequency. Others have correlated individual differences in stereopsis and binocular function with individual variability in accommodation and vergence, strabismus, dyslexia, artistic talent, and driving performance (Wilmer & Berens, 1920; Henson & Williams, 1980; Rutstein & Eskridge, 1984; Buzzelli, 1991; Livingstone & Conway, 2004; Livingstone, Lafer-Sousa, & Conway, 2011; Wright, Gooch, & Hadley, 2013; Winterbottom et al., 2014). But before this study, none examined the factors underlying disparity sensitivity functions for spatial frequency and orientation.

2. Methods

2.1. Human participants

Both experiments were performed in the Institute of Neuroscience of Newcastle University and were approved by the Ethics Committee of the Newcastle University Faculty of Medical Sciences (approval number 00625). Work was carried out in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki). Informed consent was obtained for experimentation with human subjects. All participants reported having normal or corrected to normal visual acuity. We tested 30 subjects aged between 18 and 26 years, 13 male and 17 females. One 20.4 year-old female did not participate in the second experiment.

2.2. Apparatus

Experiments were carried out in a dark room. Stimuli were presented on a 23-inch LG 3D monitor (D2342P) of the passive pattern-retarder type, with left and right images row-interleaved and separated by circular polarization. The spatial resolution of the monitor was 1920 × 1080 pixels (51 cm × 28.5 cm) and the refresh rate was 60 Hz. Observers sat at a viewing distance of 100 cm, so that a pixel subtended 0.05°. Participants used a forehead- and chin-rest and wore appropriate passive 3D glasses. They recorded their responses by pressing the left or right button of a standard computer mouse. All experiments were programmed in Matlab (R2012b) (www.mathworks.com) with the Psychophysics Toolbox extensions (www.psychtoolbox.org) (Pelli, 1997; Brainard, 1997; Kleiner, Brainard, & Pelli, 2007) and run on a DELL workstation with a NVIDIA Quadro K600 graphics card.

2.3. Stimuli and procedure (general)

The stimuli were static random dot stereograms consisting of white two-dimensional Gaussian dots each with a standard deviation of 1 arc min, with a density of 30 dots/deg² and without overlapping, presented on a black background. The disparity structure of the stimuli is described for each experiment below. The 3D was rendered with the monitor in standard 2D mode, using the line-interleaved stereo mode of Psychtoolbox’s Psychimaging function. That is, our software generated left and right stimuli each 1920 pixels wide by 540 high, and interleaved them row by row to produce a single 1920 × 1080 image to send to the monitor. We did not use the monitor’s own 3D function.

Thresholds, defined as a performance of 82% correct on two-interval forced choice tasks (2IFC), were estimated by an adaptive Bayesian staircase procedure, as described in Serrano-Pedraza et al.
2.4. Experiment 1: Threshold for corrugation detection

We measured participants’ threshold for horizontally- and vertically-oriented depth corrugations defined by horizontal disparity for a range of frequencies (0.1, 0.2, 0.4, 0.8 and either 1.2 or 1.6 cycles per degree of visual angle [cpd]), resulting in a total of ten conditions. (11 participants saw corrugations of 1.2 cpd, while 19 saw corrugations of 1.6 cpd. These corrugations were coded as 1.4 cpd in analyses that follow). Anaglyph versions of stimuli used in the experiment are shown in Fig. 1.

Each threshold was estimated from one 40-trial staircase, with thresholds for each condition obtained in ten separate tests. The ten conditions were always performed in the same order: from lowest to highest spatial frequency, first horizontal, then vertical. Participants were given time to rest between each test so as not to become weary or mentally fatigued. The time taken to complete all ten tests took between 30 and 45 min. We used a two-interval forced choice task (2IFC) where each trial consisted of two presentations, one containing the disparity grating and one depicting a plane with zero disparity; the task where each trial consisted of two presentations, one containing the disparity grating and one depicting a plane with zero disparity; the task was to indicate whether the first or the second interval contained the grating. Threshold was defined as the relative disparity between peaks and troughs which is required for performance at 82% correct.

2.5. Experiment 2: Step-edge discrimination task

In this experiment, we measured stereocuity using a horizontal and vertical ‘step task.’ Subjects were presented with a random dot pattern 540 x 540 pixels which was split centrally; one half of the pattern appeared to be in front of the screen and observers were asked to indicate which half was closer (Fig. 2). Each stimulus was preceded by a fixation cross and the stimulus remained on screen until the participant had given their answer. Adaptive Bayesian staircases, this time with fifty trials, were again used to obtain the threshold for the relative disparity between the two surfaces, in arc sec. Again, participants first recorded the threshold for a horizontal (top/bottom) step and then that for a vertical (left/right) step.

Other things being equal, we would expect naïve participants to improve with practice. Thus, this ordering may have reduced the stereo anisotropy in this data-set by enhancing (i.e. reducing) vertical thresholds relative to horizontal ones. For the same reason it reduces between-individual variability in the anisotropy compared to a random ordering (where people who did the vertical step first would be slightly biased towards higher anisotropies than those who did the horizontal step first).

3. Results

3.1. Mean disparity threshold functions (Experiment 1) and means for step-edges (Experiment 2)

Fig. 3A shows mean log disparity sensitivities in log10(arsc) as a function of spatial frequency for both horizontal and vertical disparity corrugations. The data points are means of thirty participants. Data from Bradshaw and Rogers (1999, n = 6) are shown for comparison in Fig. 3B. Thresholds for our subjects (3A) are higher than Bradshaw & Rogers (3B), likely reflecting that nearly all our 30 participants had no prior experience in visual psychophysics, whereas 4 out of their 6 participants were experienced observers. As is the case for most disparity threshold functions, the threshold functions for horizontal and vertical corrugations in both studies show a bandpass shape. Additionally, there is anisotropy, with significantly lower thresholds (higher sensitivity) for horizontal than vertical corrugations (means: 1.58 log10 arc sec for horizontal, 1.89 for vertical; t(29) = 4.03, p < 10^-3, paired t-test on log thresholds). The anisotropy in our study is rather small: a mean log-ratio (V/H) of 0.3 in Fig. 3A, compared to around 0.5 in Bradshaw & Rogers (Fig. 3B) and in another data-set from our own lab (Serrano-Pedraza et al., 2016). As noted in the Methods, our use of a fixed ordering may have tended to reduce the anisotropy. However, the difference is also not surprising given the variability of the anisotropy within the population. Hibbard, Sco-Brown, Haigh, and Adrian (2014) found that the standard deviation of the anisotropy was around 0.4. Suppose the true population mean is 0.4 and the distribution is Gaussian. Then, the 95% confidence interval for the sample mean in a 30-subject study like ours would be [0.26, 0.54], while for a 6-subject study like Bradshaw & Rogers’ it would be [0.08, 0.72]. Thus, the observed sample means of 0.3, 0.5 are entirely consistent with the same underlying distribution.

Fig. 4 shows thresholds for vertical and horizontal steps for 28 participants (Experiment 2), with the data from one individual with extreme scores not shown. 21 of 29 participants showed higher thresholds (lower sensitivity) for vertical than horizontal step stimuli, and the overall difference between groups was significant (means were 1.7 log10 arc sec vertical, 1.5 horizontal (see also Table 1); t (28) = −2.345, p = .013, one-tailed test).
3.2 Analyses of individual differences (covariance analyses)

3.2.1 Correlations, all variables (Experiments 1 and 2)

As the first step in our covariance analysis of individual differences (of systematic variability in the log disparity thresholds), we calculated correlations across the N = 30 subjects for each spatial frequency × orientation combination against each other spatial frequency × orientation combination (Experiment 1). Because 29 participants ran in both experiments, we were able to calculate correlations for each spatial frequency × orientation combination with the horizontal and vertical thresholds. The correlation matrix was computed from the log thresholds, and is shown in Table 1. Correlations significant at the \( p < .05 \) level, using one-tailed tests, are shown in bold.

Table 1 indicates that all correlations are positive, even when not statistically significant. In other words, an individual who tends to have a high or low disparity threshold compared to the group for any stimulus, will tend to show that same pattern relative to the group for all stimuli. This complete pattern positive correlations is highly unlikely to be attributable to chance, which would most likely lead to an equal number of positive and negative correlations near zero.

It appears that the 3 or 4 lowest spatial frequency stimuli correlate somewhat more strongly with each other than with the one or two highest spatial frequencies tested, while the higher spatial frequency stimuli correlate somewhat more strongly with each other. These results begin to suggest that a single statistical factor underlies performance at all low spatial frequencies tested, while a second factor contributes to detecting the highest spatial frequency. The unevenness and clustering of positive correlations, and the finding that all correlations are positive, may indicate that the underlying separate factors are not fully independent, but rather separable but interdependent (Peterzell & Teller, 2000).

It also appears that there is no noticeable effect of orientation. In general, individual differences at one orientation predict individual differences at orthogonal orientations, indicating that the factors or mechanisms underlying orientation are not independent or separate.

The patterns in data just described can also be seen in Fig. 5. It contains a scatterplot matrix of individual thresholds, and shows the data and best fitting lines used to generate the correlation matrices in Table 1. Each panel shows the scatterplot of thresholds and best-fitting line for two variables from Experiment 1. From left to right, and top to bottom are shown: Vertical 0.1 cpd, Horizontal 0.1 cpd, Vertical 0.2 cpd, Horizontal 0.2 cpd, etc., to Horizontal 1.4 cpd. Stimulus parameters are also identified on the diagonal. Within a region (Orange or Purple, corresponding to Factors 1 and 2 from the following section on factor analysis), individual differences in threshold for any orientation/SF condition correlate positively with thresholds for any other condition. Although all thresholds for all conditions correlate positively, one region of especially high correlation (Orange) is defined by all frequencies at and below 0.4 cpd, and a second region of especially high

Fig. 2. A pictorial representation of the step-edge task; (A) bottom half of the stimulus is closer; (B) left half of the stimulus is closer.

Fig. 3. Mean disparity thresholds as a function of spatial frequency for horizontal (dashed lines, open circles) and vertical (solid lines, solid circles) sinusoidal corrugations. (A) For 30 participants in Experiment 1, and patterns shown in Fig. 1, and (B) for comparison, 6 participants from Bradshaw and Rogers (1999, 20 deg field size). Log values tended to normalize distributions and render variability across conditions homogenous (homoscedastic). For each point, standard deviations ranged from 0.24 to 0.44, and standard errors ranged for 0.04 and 0.07.

Fig. 4. Mean disparity thresholds for horizontal and vertical step patterns (Experiment 2, patterns shown in Fig. 2) for 28 observers. A 29th participant with extreme scores (3.26 horizontal, 5.39 vertical) is not shown. The solid line marks the identity line. The correlation for all 29 data-points is \( r(28) = 0.88, p < 10^{-3} \) as shown in Table 1; without the outlier, \( r(27) = 0.63, p < 10^{-3} \), one-tailed tests.
correlation (Purple) is defined by frequencies at 0.8 and 1.4 cpd. Thus, the two statistical factors reported in the next section seem to reflect true variability within the data.

Thresholds for the horizontal and vertical step-edge stimuli (Experiment 2), which theoretically contain many spatial frequencies of a single orientation, correlate with each other, but not with thresholds for sinusoidal corrugations (Experiment 1). It seems that they share an underlying statistical factor, but do not clearly share this factor with the mechanisms that detect sinusoidal corrugations.

3.2.2. Factor analysis (Experiment 1)

A statistical factor analysis, which derives variability sources (or factors) from the data, was performed on the data from Experiment 1, observing procedures used in previous analyses (Peterzell et al., 1991, 1993, 1995, 2000; Peterzell, 1993; Peterzell & Teller, 1996, 2000; Peterzell, 2016). In the first step of this analysis, a principal component analysis (PCA) was performed on the data. Two of the principal components were judged significant: (A) The first two factors were the only ones with eigenvalues greater than 1 (i.e., greater than the mean), and (B) these two were the only ones to rise above the “scree” in visual scree tests. (C) Additionally, maximum likelihood Goodness of fit tests

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**Table 1**

Correlations ($r$) among log thresholds for spatial frequency X orientation variables (Experiment 1) and step stimuli (Experiment 2), with means and standard deviations. Correlations with $p < .05$ for 1-tailed tests shown in bold.

<table>
<thead>
<tr>
<th>Stimulus</th>
<th>M</th>
<th>SD</th>
<th>0.1 H</th>
<th>0.1 V</th>
<th>0.2 H</th>
<th>0.2 V</th>
<th>0.4 H</th>
<th>0.4 V</th>
<th>0.8 H</th>
<th>0.8 V</th>
<th>1.4 H</th>
<th>1.4 V</th>
<th>Step H</th>
<th>Step V</th>
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<tr>
<td>Sinusoidal Corrugations</td>
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<td>0.1 cpd, Horiz.</td>
<td>1.28</td>
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<tr>
<td>0.1 cpd, Vert.</td>
<td>1.59</td>
<td>0.44</td>
<td>0.34</td>
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<td>0.2 cpd Horiz.</td>
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<tr>
<td>0.2 cpd Vert.</td>
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<td>0.63</td>
<td>0.58</td>
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<tr>
<td>0.4 cpd, Horiz.</td>
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<td>0.30</td>
<td>0.48</td>
<td>0.62</td>
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<td>0.70</td>
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<tr>
<td>0.4 cpd, Vert.</td>
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<td>0.27</td>
<td>0.63</td>
<td>0.49</td>
<td>0.58</td>
<td>0.81</td>
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<tr>
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<td>0.51</td>
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<tr>
<td>Vertical Step</td>
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<td>0.04</td>
<td>0.03</td>
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</table>

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**Fig. 5.** Scatterplot matrix of individual thresholds from Experiment 1, showing the data and best-fitting lines used to generate the correlation matrices in Table 1. Each panel shows the scatterplot of thresholds and best-fitting line for two variables from Experiment 1. From left to right, and top to bottom are shown: Vertical 0.1 cpd, Horizontal 0.1 cpd, Vertical 0.2 cpd, Horizontal 0.2 cpd, etc., to Horizontal 1.4 cpd. Stimulus parameters are also identified on the diagonal, in bold. Within a region (Orange or Purple, corresponding to Factors 1 and 2 from the following section on factor analysis), individual differences in threshold for any orientation/SF condition correlate positively with thresholds for any other condition. Although all thresholds correlate positively, one region of especially high correlation (Orange) is defined by all frequencies at and below 0.4 cpd, and a second region of especially high correlation (Purple) is defined by frequencies at 0.8 and 1.4 cpd. Thus, the two statistical factors reported in the next section (factor analysis) seem to reflect true variability within the data, when compared to the factors in Fig. 6. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
revealed that there was significant variance in the reduced \( R \) (with communalities in the diagonal) after one factor had been extracted, \( \chi^2(35) = 52.7, p = .028 \), whereas there was no significant variance in the reduced \( R \) after 2 factors had been extracted, \( \chi^2(34) = 8.9, p = .370 \).

The statistically significant components were then rotated to Thurstonian simple structure using the Varimax criterion, a procedure akin to “sparse coding” because it maximizes the number of zero or non-zero loadings in a way that often yields interpretable and “correct” factors (Gorsuch, 1983). To investigate the possible interdependence of factors, the significant components were further allowed to inter-correlate using the Direct Oblimin criterion (Gorsuch, 1983), in a manner resembling “independent component analysis” (ICA). Because these factor-analytic statistics provided estimates of how many significant factors were contained in the data, they were used to estimate the minimum number of disparity channels required to model spatial frequency data.

Thus, from the PCA, two significant factors were extracted, accounting for the majority (70.39%) of the variability in the data set, with the first and second Varimax-rotated factors accounting for 42.45% and 27.94% of the variability, respectively. The resulting Varimax-rotated factor loadings are shown in Fig. 6A. Each factor loading represents the correlation between an input variable (i.e., the data for one of the ten spatial frequencies \( \times \) orientation corrugation stimuli) and a factor (i.e., one of the factors obtained from the Varimax-rotated PCA).

Each of the two Varimax-rotated factors in Fig. 6A shows clear spatial frequency tuning – their factor loadings vary systematically with spatial frequency. A single factor (Factor 1) accounts for nearly all of the variability at and below 0.4 cpd, regardless of orientation. Including the crossover at just below 0.8 cpd, the second factor accounts for most of the variability at higher spatial frequencies. The oblique solution (Fig. 6B) provided loadings very similar to the orthogonal one (Fig. 6A), but showed that the factors are strongly intercorrelated, \( r(29) = 0.53, p < .05 \), and thus not independent.

Split-half analyses were performed to examine the reliability of the 2-factor result. Correlational and factor analyses were repeated on data for (1) the first fifteen and (2) the second fifteen participants, and for (3) the fifteen odd-numbered participants and (4) the fifteen even-numbered participants, and for (5) the seventeen male participants and (6) the thirteen female participants. In general, two factors were obtained, with factors tuned to high and low spatial frequencies but not orientation, but with considerable variability in the tuning of the high and low frequency factors. As such, while the two-factor solution with its spatial frequency selectivity seems likely to be correct, we emphasize that the solution may change somewhat with a larger and thus more stable sample.

4. Discussion

We have measured disparity thresholds for 30 individuals. As shown in Fig.3A, the average threshold functions contain (1) bandpass tuning for spatial frequency, and (2) an anisotropy such that sensitivity is higher for horizontal than vertical stimuli, both in sinusoidal corrugation and step-edge stimuli. These findings are generally consistent with previous literature on stereoscopic sensitivity and anisotropy (Tyler, 1974; Rogers & Graham, 1982; Bradshaw & Rogers, 1999; Serrano-Pedraza et al., 2013, 2016; Rogers & Graham, 1983; Mitchison & McKee, 1990; Gillam & Ryan, 1992; Cagenello & Rogers, 1993; Hibbard et al., 2002; Witz & Hess, 2013; Witz, Zhou, & Hess, 2014; Tyler & Kontsevich, 2001).

However, our primary goal was to examine individual variability in our data to infer the number and tuning of stereoscopic mechanisms, as well as the interactions among these mechanisms. We have analyzed correlations between disparity thresholds on different tasks – depth discrimination of a horizontal and vertical step-edge, and detection of horizontal and vertical depth corrugations. In the corrugation data, our factor analysis revealed just two significant, interpretable factors, which together account for about 70% of the variability in the data. As shown in Fig. 6, one factor is tuned to low spatial frequencies (\( \leq 0.4 \) cycle per degree) and the other to high spatial frequencies (\( \geq 0.8 \) cpd). The factors are not selective for orientation despite the anisotropy, an unexpected finding. The factors, while separate, are not independent of each other, as determined by examining the correlation matrix and also from the results of an orthogonal rotation of factors. If an individual has high or low sensitivity for one factor relative to the group, he or she will also tend to have high or low sensitivity for the other factor relative to the group (Peterzell & Teller, 2000).

4.1. Underlying neural mechanisms

Factor analysis can reveal distinct channels or neural mechanisms, but cannot prove their absence. For example, suppose two perceptual tasks are supported by different neural populations, with sensitivity reflecting the number of neurons in the population. If the number of neurons in each population, and thus the sensitivity, is perfectly correlated across individuals, this will produce only a single factor, even though other psychophysical techniques, such as adaptation or masking, would reveal the presence of two distinct populations. With that in mind, we consider how the two factors we have identified can be interpreted within the framework of our existing knowledge about disparity encoding.
Previous literature indicates that disparity is processed within two or more distinct spatial-frequency channels (Julesz & Miller, 1975; Schumер & Ganz, 1979; Pulliam, 1982; Yang & Blake, 1991; Cobo-Lewis & Yeh, 1994; Shioiri, Hatori, Yaguchi, & Kubo, 1994; Tyler, 1994; Norcia, Sutter, & Tyler, 1985; Glenerster & Parker, 1997; Prince, Eagle, & Rogers, 1998; Wilcox & Allison, 2009; Serrano-Pedraza et al., 2013; Witz et al., 2014). The bandwidth of a channel is often estimated to be ~2 octaves. For example, Witz et al. (2014) concluded that spatial frequencies of 0.25 cpd and 0.5 cpd (1 octave apart) are visible to the same channel, whereas spatial frequencies of 0.25 cpd and 1 cpd (4 octaves) are detected by different channels. Here, we find that the same factor loads roughly equally onto 0.1, 0.2 and 0.4 cpd, but much less for 0.8 and 1.4 cpd, consistent with the idea that 1 cpd is detected by a different channel than 0.25 cpd. Neuronal terms, these different channels presumably correspond to neurons tuned to different frequencies of disparity modulation, with the bandwidth of the channel determined by the bandwidth of the individual neurons. These neurons may be located in higher visual areas which are selective for disparity-defined slant and/or curvature (Orban, 2011). In monkey, these include the intraparietal sulcus (the caudal and anterior intraparietal areas, CIP and AIP [Taïr, Tsutsui, Jiang, Yar, & Sakata, 2000; Durand et al., 2007; Nakamura et al., 2001; Tsutsui, Taïr, & Sakata, 2005]), the inferior temporal gyrus (notably TEs; [Liu, Vogels, & Orban, 2004; Janssen, Vogels, & Orban, 2000]), and ventral premotor cortex area F5 (Theys, van Loon, Goffin, & Janssen, 2012, 2013; Joly, Vanduffel, & Orban, 2009). Broadly consistent properties have been found in human studies with fMRI (Chandrasekaran, Canon, Dahmen, Kourtzi, & Welchman, 2007).

The fact that our analysis reveals two distinct factors for spatial frequency implies that the corresponding neural mechanisms are somewhat decorrelated within an individual. For example, an individual may have good sensitivity for low-frequency corrugations, perhaps reflecting that they have an unusually large number of neurons tuned to these frequencies, and yet still have poor sensitivity for high-frequency corrugations. For this reason, two factors are needed to describe their performance.

Surprisingly, however, we do not find different factors for horizontal and vertical corrugations. This is because thresholds for horizontal and vertical corrugations at the same frequency are highly correlated, as are thresholds for horizontal and vertical step-edges. This is surprising because our understanding of stereoscopic physiology indicates that these thresholds are mediated by distinct neuronal populations: we expect individual neurons in the higher visual areas listed above to be tuned to horizontal or to vertical disparity gradients, but not to both. In theory, corrugations could be detected by neurons with isotropic tuning to disparity gradients, e.g., a Mexican hat profile, but this would not explain the stereo anisotropy: the higher thresholds for vertical gradients presumably reflect different neural mechanisms. The neuronal basis of the stereo anisotropy is not known, but a simple possibility would be that the relevant areas of visual cortex tend to contain more “slant” neurons than “tilt” neurons.

If horizontal and vertical corrugations are detected by different neuronal populations, but thresholds are highly correlated across individuals, this indicates correlation in the properties of the underlying neuronal populations. For example, in the simple model of the stereo anisotropy proposed above, the interpretation would be that although everyone has more slant than tilt neurons, people who have more slant neurons than average also have more tilt neurons than average.

It is true that the stereo anisotropy is very variable between individuals, which in this account would imply variability in the ratio of slant to tilt neurons. This variability would have to show up as a factor in a suitably-powered study. Our study was not suitable for finding this factor, since in our data the anisotropy is manifest at only one spatial frequency, 0.1 cpd, as shown in Fig. 3A. A factor representing individual variability in stereo anisotropy can therefore only really predict one set of results (thresholds at 0.1H given thresholds at 0.1 V); it has little predictive power and is thus not likely to be found. If we had measured thresholds at more, lower frequencies, then such a factor would have had more predictive value and would thus be more likely to emerge from our analysis.

4.2. Implications for clinical and industrial applications, and caveat regarding “true” individual differences

Our results have implications for the efficient characterisation of stereo vision via the disparity sensitivity function, e.g., to investigate whether an individual’s stereoscopic abilities predict their performance in aviation or surgery. Although thresholds in Experiment 1 were measured for ten stimulus conditions (i.e., 2orientations × 5 spatial frequencies), the individual differences underlying disparity sensitivity functions can be represented by just two factors, plus error. Thus, if one were going to make just two measurements to capture the disparity sensitivity function, these should be at low-frequency (e.g. 0.1 cpd) and high-frequency (e.g. 1.3 cpd). The orientation does not matter: to this degree of accuracy, one can assume that the threshold will be the same for both horizontal and vertical gratings at 1.3 cpd, and about a factor of two higher for vertical at 0.1 cpd. Obviously, more measurements would capture more data about the individual, but our study shows these are the two measurements to begin with.

4.3. Comparison to a recent study by Reynaud and Hess (2017)

Following our initial report of the data reported here (Read, Serrano-Pedraza, Widdall, & Peterzell, 2016), Reynaud and Hess (2017) reported an analysis similar to our own. They factor-analysed their own archival quick Disparity Sensitivity Functions (qDFSs) for 61 participants (Reynaud, Gao, & Hess, 2015). To obtain sensitivities, participants discriminated between 45° and 135° oblique sinusoidal corrugations embedded in carriers composed of 2-D fractal noise. Their stimuli and procedures used to measure disparity sensitivities were different than ours, in that we measured separate sensitivities for horizontal and vertical sinusoidal corrugations embedded in dots. Spatial frequencies ranged between 0.24 and 2.39 cpd. The factor analysis methods of Reynaud and Hess appear to be nearly identical to our own, with the two most significant factors obtained from a principal component analysis (PCA) accounting for 91% of the variability in the data set, and rotated to approximate simple structure using the Varimax rotation. Like us, they found evidence to suggest that the two factors are intercorrelated, but they found this not through examining an oblique rotation (as we used) but rather through correlating beta weights for the two factors. Reynaud and Hess further conducted a hierarchical clustering analysis and generated a dendrogram to provide additional evidence of 2–3 factors, and they used the Moore-Penrose pseudo inverse equation to demonstrate that the two factors can closely reproduce the original data.

The factor analytic results of Reynaud and Hess are compared to our own in Fig. 7. The studies are consistent in that both report two spatial frequency tuned factors. It is apparent in Fig. 7A that the factors obtained in the two studies do not match when spatial frequency is classically defined in terms of retinal size, or cycles per degree of retinal angle. Some may view the resulting differences as moderate, reflecting differences in methods (i.e., discriminating two types of oblique patterns vs. determining sensitivity for horizontal and vertical gratings separately), different mechanisms (i.e., disparity mechanisms detecting oblique gratings vs. those detecting horizontal and vertical gratings), or other procedural differences.

Reynaud and Hess discuss previous evidence (e.g. from Yang & Blake, 1991) to suggest that additional spatial frequency tuned processes may lie beyond the range of spatial frequencies they tested. It seems likely that if a third factor had reached significance in their analysis, then this factor would have loaded selectively on their one or
two lowest spatial frequencies, and thus could have resembled our Factor 1. This seems likely because (1) the two reported factors are near zero at their two lowest spatial frequencies, meaning that an additional factor would need to explain variability at low spatial frequencies, and (2) a visual inspection of their Fig. 1 seems to show the possibility of a weak factor at their one or two lowest spatial frequencies.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.visres.2017.11.002.

References

Pelli, D. H., Chang, S. K., & Teller, D. Y. (2000). Spatial frequency tuned covariance...


