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OBSERVATION

Redundant Visual Information Enhances Group Decisions

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Important perceptual judgments are often made by combining the opinions of several individuals to make a collective decision, such as when teams of physicians make diagnoses based on medical images. Although group-level decisions are generally superior to the decisions made by individuals, it remains unclear whether collective decision making is most effective when information is redundantly provided to all individuals within a group, or when each individual is responsible for only a portion of the total information. Here, we test this idea by having individuals and groups of different sizes make perceptual judgments about the presence of a weak visual signal. We found that groups viewing the entirety of information significantly outperformed groups that viewed limited portions of information, and that this difference in performance could be accounted for by a simple internal noise-averaging model. However, noise averaging alone was insufficient to account for improvements in individual and group-level performance as group size varied. These results indicate that sharing redundant information can enhance the quality of individual perceptual judgments and lead to better group decision making than dividing information across members of a group.

Keywords: signal detection, efficiency, collective decision making

Aggregate group-level decisions are typically considered to be superior to individual decisions across a wide variety of domains (Clemen, 1989). This so-called "wisdom of the crowds" effect (Surowiecki, 2004) is put into practice when groups of people are trusted to make important real-world decisions, such as juries rendering verdicts or teams of radiologists reading X-rays. Although the advantage of using groups in place of individuals is often attributed to a statistical improvement that results from aggregating the contributions of individual group members (Green & Swets, 1966; Lorge & Solomon, 1955; Sorkin, Hays, & West, 2001; Swets, Shipley, Mckey, & Green, 1959), there is also evidence that social interactions may play a role in enhancing group decisions, such as when the performance of the group falls below that of the best member (Bahrami et al., 2010; Lorenz, Rauhut, Schweitzer, & Helbing, 2011) or exceeds the expectation of the individual group members working in isolation (Collins & Guetzkow, 1964; J. H. Davis, 1992). Further, the extent to which groups benefit from the introduction of additional members has been shown to depend on the type of decision rule adopted by the group (Sorkin, West, & Robinson, 1998) and whether or not communication was permitted among group members (Bahrami et al., 2012).

Several recent experiments have explored the influence of group-level processes on the quality of decisions made by pairs of observers (Bahrami et al., 2012; Bahrami et al., 2010) and larger groups of observers (Sorkin et al., 2001; Sorkin et al., 1998) about perceptual events. In these experiments, each observer typically received an identical copy of the stimulus and individuals and groups were asked to distinguish between two alternatives. For pairs of observers, performance varied depending on how well-calibrated individual confidence estimates were within the group, with more consistent groups outperforming their better group member (Bahrami et al., 2010). Extending the group size beyond a pair was also shown to increase the group performance at a cost of lowering efficiency relative to a theoretical group of the same size (Sorkin et al., 2001).

The results of such experiments have provided convincing evidence that presenting individuals with the same perceptual information improves the quality of collective decisions beyond the contributions made by the individual members of the group. But might there be ways to further enhance the efficiency of group-level decision-making? One possibility, which we have considered here, would be to render the information provided to individuals nonredundant—that is, by splitting the information up across individuals within a group. On the one hand, distributing the stimulus in such a way might serve to improve the efficiency of each individual member of the group, by allowing them to focus exclusively upon a subset of the information rather than having to divide their attention across the entirety of the stimulus (Davis, Kramer, & Graham, 1983; Posner, Snyder, & Davidson, 1980). On the other hand, any statistical benefits that the group is able to achieve

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Both authors contributed to the idea and design of the experiments, and the writing and editing of the manuscript. Shawn Barr programmed the experiments and collected and analyzed the data.

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by having information presented redundantly to all members of the group would be lost when information is divided up across individuals within the group. That is, unlike the redundant case, in which variability in group member ability may actually enhance group decision making (Sorkin & Dai, 1994), differences in individual ability may ultimately limit the overall performance of the group when information is distributed across members, because the group will be forced to rely on the abilities of each individual member for some proportion of the time. Thus, the goal of our experiments was to explore whether distributing information across the individual members of a group would serve to enhance or reduce the quality of group-level decisions that are made about perceptual events.

Experiment 1

Our first experiment was designed to explore the impact of information redundancy and number of observers on the efficiency of group decision-making in a simple perceptual task. We asked groups of observers to make both individual and collective judgments about the presence of a noisy Gaussian blob located at one of *N* possible locations on a computer display. We varied the number of observers participating in the experiment (from one to four) and tested observers in two separate conditions: one in which each observer viewed the stimulus in its entirety (the *full* condition) and one in which each observer viewed only a single, fixed location (the *partial* condition). In both cases, observers first made individual decisions about the presence of the Gaussian blob, followed by a collective decision made by the group as a whole.

Method

Participants. A total of 232 subjects participated in these experiments. Data from 11 subjects were dropped due to unreliable threshold estimates (see the Performance measures section below). Participants were undergraduate students at Indiana University with normal or corrected-to-normal visual acuity. All were naive to the purpose of the experiment, and gave informed consent prior to their participation.

Task, stimuli, and procedure. Groups of one to four observers performed a simple signal detection task (Green & Swets, 1966). To ensure that only one monitor was visible to each subject, four monitors were positioned so that each monitor faced a different side of a table. Observers were seated at an average distance of .7 m from their designated monitor and viewed a square display that was carved into equal-sized quadrants (256 × 256 pixels, 6.3° × 6.3°) for ~500 ms. The total number of quadrants that appeared in the stimulus presentation was equal to the size of the group (see Figure 1). A sample of high-contrast Gaussian white pixel noise appeared in each quadrant during the stimulus presentation. The observers' task was to detect the presence or absence of a Gaussian luminance bump (the signal) added to the center of one of the noise quadrants with equal probability.

Groups of observers participated in one of two possible conditions: the full-information condition, in which an identical copy of the entire stimulus (signal + noise) was presented to each observer in the group; or the partial-information condition, in which the stimulus was separated into quadrants (or parts), with each observer viewing only a single, unique quadrant. In both conditions,

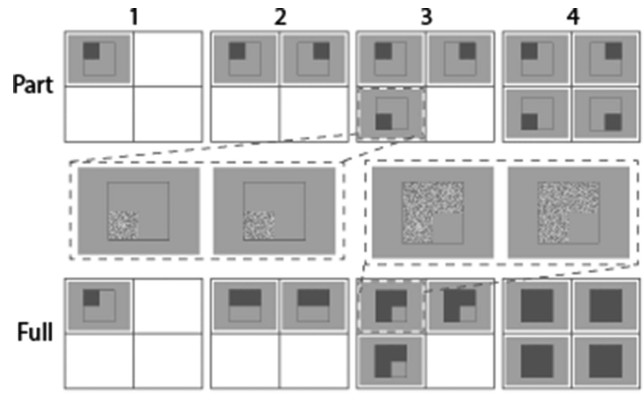

Figure 1. The top three rows illustrate the stimulus layout for different sized groups. The shaded regions in rows 1 and 3 indicate the location of the stimulus. In the experiment, the shaded region was replaced with an actual stimulus. Examples of a present and absent stimulus shown to an individual observer for a group size of three are shown in the second row. (Signal present on the left and signal absent on the right.)

individual observers initially made their own separate decisions about the presence or absence of the signal. Afterward, the members of the group were allowed to freely discuss what they had seen, and then a final group-level decision was made by a randomly chosen member of the group. Written feedback about the correctness of the group decision was provided along with visual feedback indicating the true location of the signal (on signal-present trials).

Performance measures. The performance of each group was evaluated by varying the contrast energy (i.e., integrated squared contrast) of the signal across trials to obtain a detection threshold. We controlled for the varying amount of stimulus information available to groups of different sizes by comparing performance to that of an *ideal observer*—a theoretical machine that makes statistically optimal use of stimulus information (Geisler, 1989; Green & Swets, 1966). The ideal strategy for our task and stimuli involves comparing the stimulus on each trial with an absent (blank) template and a signal template for each possible signal location, and then selecting the alternative (present or absent) with the greater posterior probability (Braje, Tjan, & Legge, 1995; Green & Swets, 1966). The ratio of ideal to human threshold (a quantity known as *efficiency*) yields the proportion of information used by the group of human observers, and is independent of the intrinsic difficulty of the task (Tanner & Birdsall, 1958).

Results and Discussion

Figure 2a plots thresholds as a function of group size for the ideal observer (dotted line) and groups of human observers in both the partial (dashed line) and full (solid line) information conditions in Experiment 1. These data show that thresholds for the human observers in both the partial and full conditions decreased when a second member was added to the group. However, this trend continued only in the full condition, in which thresholds continued to decrease as group size increased. Unlike human observers, thresholds for the ideal observer systematically increased as a function of group size due to the increasing negative effects of uncertainty about the location of the signal (Pelli, 1985). The

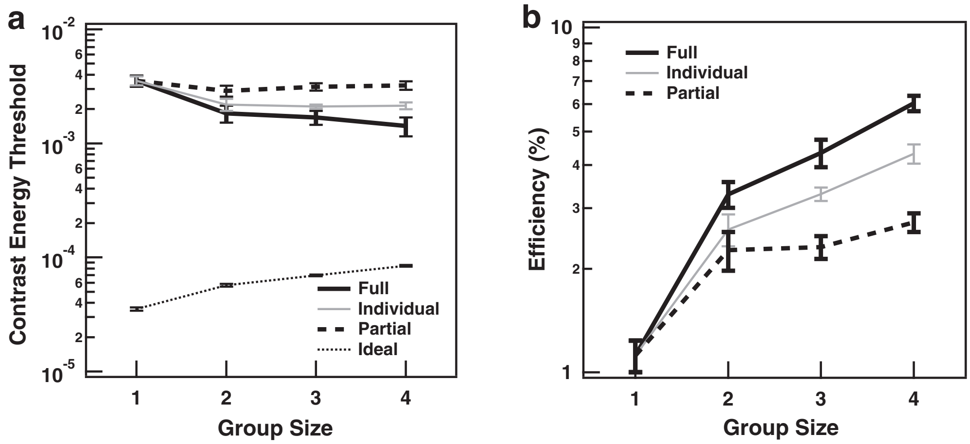

Figure 2. Mean thresholds (a) and efficiencies (b) for the full and partial information conditions for each group size. Thresholds (a) in both conditions increased as a second member was introduced to the group, and tended to increase further for larger groups in the full but not partial conditions. However, the amount of contrast energy required by the ideal observer for this task also increased with the number of possible target locations, as indicated by the ideal line in (a). When the total amount of information available from the stimulus was taken into account, groups in both conditions tended to be more efficient as group size increased (b). Error bars on each symbol correspond to ± 1 *SEM*.

combined effects of information availability (i.e., the ideal observer's thresholds), and the human observers' collective ability to make use of information are reflected in the efficiencies, plotted in Figure 2b. These data show that efficiency systematically increased with group size in both conditions, with the most dramatic increase in efficiency resulting from the introduction of a second observer. However, efficiency for all group sizes was greater in the full condition than the partial condition, and this discrepancy grew as the number of members within the group increased. These effects are illustrated by the solid line in Figure 3b, which plots the ratio of full/partial efficiency as a function of group size. A 3 (Group Sizes 2–4) $\times$ 2 (full and partial information) ANOVA

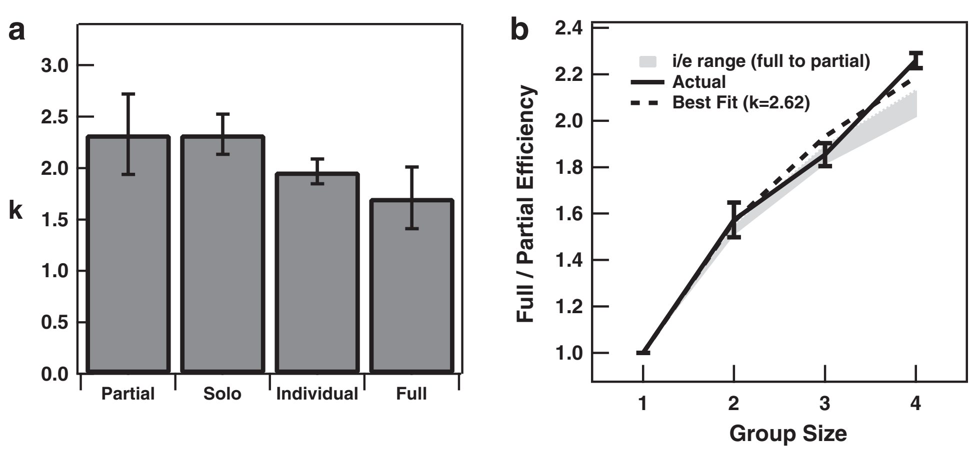

Figure 3. (a) Experimental estimates of $k = \sigma_I^2/\sigma_E^2$ for the full and partial conditions were from groups with two members. This ratio was also calculated for each member of the pair (individual) in the full condition. Estimates for participants performing the task on their own (solo) were also provided for stimuli composed of one and two quadrants. The second quadrant was included to control for the possibility that the level of internal noise depended on the size of the stimulus. However, because the difference between the two stimulus sizes was not statistically significant, $t(17.2) = .41$, $p = .69$, these estimates were combined. Error bars in both figures correspond to ± 1 *SEM*. (b) Comparison of actual and predicted efficiencies based on estimates of $k = \sigma_I^2/\sigma_E^2$, the internal/external noise ratio, estimated by double-pass response consistency. The dashed line shows the model predictions for the single value of $k = \sigma_I^2/\sigma_E^2$ that best predicts the ratios of full to partial efficiency from our human observers. The gray region below this line shows the range of predictions obtained by substituting the empirical estimates of $k = \sigma_I^2/\sigma_E^2$ (Figure 3a) into Equation (4). The solid line with error bars shows the empirical efficiency ratios from the experimental data (Figure 2b).

confirmed that there were highly significant main effects of both group size, $F(2, 49) = 15.67$, $p < .001$, and information condition, $F(1, 49) = 90.23$, $p < .001$, as well as a significant interaction between group size and information condition, $F(2, 49) = 8.55$, $p < .001$.

Experiment 2

The results of Experiment 1 indicated that the efficiency of group-level decision making is significantly improved when the individual members of the group are given access to the entirety of information compared with when each member is exclusively responsible for only a subset of the information. Further, this positive benefit from redundant presentation of information across group members grows systematically as additional members are introduced to the group.

But why does sharing redundant information serve to significantly improve efficiency when making collective decisions about perceptual events? One possibility is that groups in the full condition gain a statistical advantage by having more chances to detect the signal than groups in the partial condition. Although all N observers viewed an identical copy of the stimulus (which was corrupted by an identical copy of externally added noise), each observer also introduced his or her own independent sample of internally generated noise (Barlow, 1957; Croner, Purpura, & Kaplan, 1993; Legge, Kersten, & Burgess, 1987; Pelli, 1990). Internal noise is an irreducible source of variability that is present in any real-world information-processing system. Previous experiments have demonstrated that internal noise is present at various levels of processing within the human visual system and places limits on how efficiently information can be used under threshold conditions (Blakemore, 1990). However, it is possible to reduce the limiting effects of internal noise by averaging across multiple instances generated for the same stimulus. Statistically, the variance of the internal noise-limiting performance can potentially be reduced by up to a factor of N (where N corresponds to the number of noise samples contributing to the decision). Such benefits of noise averaging have been demonstrated previously in the context of individual observers making multiple sequential observations when detecting a signal in the presence of noise (Swets et al., 1959).

We modeled the effects of internal noise averaging in our task by building an observer that was ideal except for internal noise (Burgess & Colborne, 1988; Geisler, 1989; Pelli, 1990). The total amount of noise limiting this observer was partitioned into an external component that was fixed according to the level of noise added to the stimulus for each member of the group, and an internal component that varied independently across individual group members. The internal noise was assumed to cover the same spatial region as the external noise presented to the observer. As a result, the inclusion of internal noise for a group of size N in the partial condition was formally equivalent to presenting an additional sample of noise that extended across the entire stimulus region to a single observer. Thus, the squared sensitivity (d'^2) of a group in the partial condition of our task could be expressed as

$$(d')^2 = m_p^2 / (\sigma_E^2 + \sigma_I^2) \quad (1)$$

and the signal energy required by the group to achieve a criterion level of squared sensitivity (d'^2_c) could thus be expressed as

$$m_p^2 = (d')_C^2 \, (\sigma_E^2 + \sigma_I^2) \quad (2)$$

where σ_I^2 and σ_E^2 are the internal and external noise variances, and m_P^2 is the energy of the signal at threshold in the partial condition (Swets et al., 1959). Alternatively, the inclusion of internal noise for a group of size N in the full condition would be formally equivalent to averaging N independent noise samples that extended across the entire stimulus region and presenting this to a single observer. Accordingly, a smaller signal energy m_F^2 was required in the full condition to match the criterion level of performance of the group (d'^2_c) in the partial condition due to a statistical reduction in the internal variability of the group response by a factor of N, i.e.,

$$m_F^2 = (d')_C^2 \, (\sigma_E^2 + \sigma_I^2 / N) \quad (3)$$

Thus, any difference between the two conditions in the performance of the internal noise-limited ideal observer would be determined solely by the statistical effects of internal noise. The statistical reduction in internal variability that occurred in the full condition due to multiple opportunities to detect the signal could also be thought of as a form of error correction, whereby mistakes would be averaged out of the group-decision process. Note that this effect would stem directly from the fact that there would be no redundancy across the stimulus regions presented to observers in the partial condition and complete redundancy across the stimulus regions presented to observers in the full condition. That is, each observer in the partial condition would view a unique part of the stimulus, and therefore the group would be unable to reap the benefits of noise averaging as in the full condition.

We tested this simple noise-averaging model by computing the ratio of full to partial efficiency for the internal noise-limited ideal observer as well as for our human observers (Figure 3b). Unlike previous accounts for the "wisdom of the crowds" effect (Surowiecki, 2004), in which group performance was compared with the statistical aggregate of individuals working in isolation (Faust, 1959; Lorge & Solomon, 1955; Sorkin et al., 2001; Sorkin et al., 1998), this ratio compared the performances of groups of the same size. Consequently, by controlling for any changes in performance that may have resulted from the collective action of the group, this ratio provided a prediction for the amount of improvement in full relative to partial information sharing expected from statistical averaging alone, i.e.

$$\frac{\eta_F}{\eta_P} = \frac{(m_I^2 / m_F^2)}{(m_I^2 / m_P^2)} = \frac{m_P^2}{m_F^2} = \frac{(d')_C^2 \, (\sigma_E^2 + \sigma_I^2)}{(d')_C^2 \, (\sigma_E^2 + \sigma_I^2 / N)} = \frac{(1 + k)}{(1 + k / N)} \quad (4)$$

where η_F and η_P are the full and partial efficiencies, and $k = \sigma_\mathrm{I}^2/\sigma_\mathrm{E}^2$, the ratio of internal to external noise (Burgess & Colborne, 1988; Green, 1964). Also note that, because the combined sample of external noise was equivalent in the two conditions, true ideal performance, $m_I^2 = (d')_C^2\sigma_E^2$ was identical across conditions.

Method

To extend this model to human observers, we first verified that d' was proportional to the signal contrast (Legge et al., 1987; Pelli, 1990), and that, although there was a slight bias toward absent responses at low contrast, this bias was consistent across conditions. An empirical estimate of σ_I^2/σ_E^2 for the human observers in our tasks was then provided by a double-pass masking technique (Burgess & Colborne, 1988; Gold, Bennett, & Sekuler, 1999; Gold, Sekuler, & Bennett, 2004; Green, 1964). Specifically, we had individual observers as well as groups of two observers (in both the full and partial information-sharing conditions) complete our signal-detection task. Unbeknownst to the observers, an identical pass through the experiment was repeated during the second half of the testing session. Because any variability in performance across identical presentations of a stimulus must be determined by internal noise, an estimate of σ_I^2/σ_E^2 could be obtained using the relation between the percentage of agreement and percentage of correct responses across two identical passes through the same sequence of stimuli (see Gold et al. (2004) for details on the procedure for calculating σ_I^2/σ_E^2).

Results and Discussion

The dashed line in Figure 3b shows the model predictions for the value of σ_I^2/σ_E^2 that offers the best fit to the ratio of full/partial efficiency produced by our human observers. The gray band below this line shows the range of predicted efficiency ratios derived from the empirical values of σ_I^2/σ_E^2 obtained from our human observers using double-pass masking (Figure 3a). These data show that the ratios of full/partial efficiency for our human observers closely agreed with the predictions of the noise-averaging model.

Although the results of our double-pass masking experiment imply that a simple noise-averaging model is sufficient to account for the advantage of full over partial information sharing, it cannot fully account for the changes in efficiency that take place as additional members are introduced into the group. Within both the full and partial conditions, the trend in efficiency departs from the prediction of the noise-averaging model. When individual group member contributions are combined into a group decision, the model predicts no change in efficiency for the partial condition. Yet Figure 2b shows a noticeable increase in efficiency when a second observer is paired with the first for both conditions. These improvements suggest that group-level decision making can lead to emergent processes that provide additional benefits not experienced by single observers.

But at what level do these benefits arise? One possibility is that pairs of observers engage in more efficient group-level interactions. A second possibility is that pairs of observers improve on an individual level, which leads to more efficient group-level decision making. An important assumption of the simple noise-averaging model is that the sensitivities of the individuals within the group do not depend upon the overall size of the group. This typically leads to the prediction that group performance is superior to individual performance by as much as $\sqrt{N}$, where N is the size of the group (Bahrami et al., 2010; Sorkin et al., 2001; Swets et al., 1959). Because group membership was not assumed to affect individual performance, individual-level efficiencies were expected to remain unchanged, regardless of group size or condition. To test this prediction, we computed individual observer thresholds by using the decisions made on each trial of our original experiment by each observer within each group before the group-level decision was made (this procedure was only possible for the full condition, as the number of signal-present trials for individual observers in the partial condition were too few to obtain reliable threshold estimates). The resulting thresholds and efficiencies are shown along with the original group-level results in Figures 2a and 2b. To test whether individual performance increased in the presence of others, the efficiency of individuals performing the task in isolation was compared to the efficiency of the individual members of a pair for both conditions. These two-sample t tests revealed that individual performance improved in the partial condition, $t(31.2) = 3.15$, $p = .003$, and even exceeded the model prediction from equation (4) in the full condition, $t(39.5) = 2.07$, $p = .02$, resembling the performance of the group more than the performance of individuals completing the task in isolation. This surprising result, consistent with the effect of social motivation (Collins & Guetzkow, 1964), shows that working collectively as a group can improve both individual and group-level decision making.

Conclusion

The results of our experiments offer several new insights about the properties of group-level perceptual judgments. Most notably, we found that the “wisdom of the crowds” effect (Surowiecki, 2004) is further enhanced by redundantly presenting information in its entirety to all members of a group. When generalizing this finding to other tasks, we might expect the benefit from redundancy to be reduced for more demanding tasks, such as serial search or situations in which a single individual would be insufficient to complete the task. Yet for a simple detection task, the additional improvements exhibited by groups who share redundant information can be accounted for by the statistical benefits predicted by averaging the internal noise associated with the group response. However, noise averaging alone was unable to account for the improvements in efficiency with increasing group size. Instead, our results suggest that the dynamics of group decision making may lead to qualitative changes in how individual observers make use of information relative to when they work in isolation. Taken together, these results provide important theoretical constraints for models of group-level perceptual decision making, as well as practical guidance for maximizing the efficiency of real-world judgments that involve group-level perceptual decisions.

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(*Appendix follows*)

Appendix

Stimuli and Apparatus

Each stimulus contained between one and four 256 × 256 pixel (6.3° × 6.3°) quadrants with each pixel containing a sample of additive high-contrast Gaussian white noise of fixed variance ($\sigma^2 = 0.0625$; Noise Spectral Density = 6.1e-04). On signal present trials, luminance at the center one of the noise quadrants was elevated by a two-dimensional Gaussian bump ($\sigma_{x,y} = 25$ pixels). The luminance l_{ij} and contrast at each pixel c_{ij} were related as, $c_{ij} = (l_{ij} - L)/L$, where the background luminance L was fixed at 49.1 cd/m^2. Stimuli were displayed on up to 4 separate CRT monitors, depending upon the number of participants. To ensure that each monitor was visible to only a single subject, the four monitors were arranged along a table so that each monitor faced a different side of the table. Each monitor had a frame rate of 85 Hz, a resolution of 1024 × 768 pixels and had a displayable region that was 31 × 24 cm in size. The monitors were calibrated using a Minolta LS-100 photometer. Each display was driven by a 2.3 GHz, dual-core Mac Mini running the Psychophysics Toolbox Version 3.0.8 (Brainard, 1997) from MATLAB (R2008b). Stimulus presentations on the four machines were coordinated through a MySQL database.

Staircase Procedure

The contrast energy of the signal was adjusted before each trial according to a 2-down 1-up staircase procedure based on a correct (hits and correct rejections) or incorrect (misses and false alarms) group response. The staircase data were then fit by a Weibull psychometric function in order to obtain a 71%-correct contrast energy thresholds estimate.

Ideal Observer Simulations

An ideal observer that followed a maximum posterior decision rule (Braje et al., 1995; Geisler, 1989; Green & Swets, 1966) was simulated 10 times for 3000 trials at each group size 1–4. Contrast energy thresholds were estimated using the same procedure described for human observers.

Experiment 1

Each experiment with groups of size 2–4 lasted ~50 minutes and consisted of 168 trials. In the full condition, there were nine groups that participated in each size of group. In the partial condition, there were 13 groups of size 2, 9 groups of size 3, and 10 groups of size 4 (3 groups of size 2 were dropped from the analyses due to unreliable threshold estimates). 15 individuals (i.e., groups of size 1) completed 160 trials of the same task, which lasted ~20 minutes (2 dropped due to unreliable threshold estimates).

Experiment 2

Only groups of size 1 or 2 participated in the second experiment. 10 groups of size 2 completed two passes thorough 160 trials in both the full and partial conditions (1 dropped from each condition due to unreliable threshold estimates). 33 individuals (i.e., groups of size 1) completed 2 passes through 350 trials. 15 of the individuals viewed a stimulus that contained only a single quadrant and the remaining 18 viewed two quadrants (3 dropped due to unreliable threshold estimates). To compare the performances of individuals within a group to those performing the task in isolation a Welch's t-test was used. Since individual chance performance depended on the group size in the partial condition, trials in which the signal appeared in the partner's quadrant were ignored. Data from 17 individuals were included (1 dropped) in the full condition. In the partial condition, however, threshold estimates were more difficult to obtain and data from 10 out of 18 individuals were included.

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