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Contour grouping: closure effects are explained by good continuation and proximity

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Abstract

Previous experimental studies have provided evidence that closed contours are easier to detect than open contours in random-element displays, and previous theoretical studies have shown that these effects might be explained by an active neural mechanism (e.g., a "reverberating neural circuit") sensitive to closure. To test this hypothesis, detection thresholds were measured in five experiments designed to control for the effects of uncertainty, eccentricity, and element density. In four of the experiments, we found that closed contours were no easier to detect than open contours, and in the remaining experiment the effects were consistent with the predictions of probability summation. Thus, we could find no evidence for an active neural mechanism that enhances detectability of closed contours more than open contours, although some form of closure mechanism may play a significant role in image interpretation.

Keywords: Perceptual grouping; Natural scene statistics; Contour integration; Closure

1. Introduction

Contour grouping has a fundamental role in perception and recognition. In order to correctly interpret images, the visual system must first group local contour elements that are likely to belong to the same physical contour. For example, recognition of even a highly familiar object is impossible if either too few of its contour elements are grouped together, or if too many of its contour elements are grouped with elements from the local context.

Recent models of contour grouping are, by and large, elaborations of the Gestalt principles of "good continuation" and "proximity" (Wertheimer, 1958)—contour elements tend to be grouped if they are nearby and consistent with a smooth contour (Elder & Goldberg, 2002; Field, Hayes, & Hess, 1993; Geisler, Perry, Super, & Gallogly, 2001; Gigus & Malik, 1991; Grossberg & Mingolla, 1985; Pettet, McKee, & Grzywacz, 1998; Sha'ashua & Ullman, 1988; Yen & Finkel, 1998). Most of these models can be regarded as having three parts: (1) extraction of local contour elements, (2) grouping locally those contour elements that satisfy certain geometrical constraints (e.g., co-circularity and proximity), and (3) formation of extended contours by linking the local groups or by propagating the local grouping over larger distances. Some of these models also include computational processes similar to the Gestalt principle of "closure"—contour elements tend to be grouped if they are consistent with a closed contour (e.g., Pettet et al., 1998; Yen & Finkel, 1998).

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The principle of closure may have ecological validity: the bounding contour of an object in isolation forms at least one closed contour (e.g., see Elder & Zucker, 1993), and hence, a rational observer might use a closure rule to facilitate the detection of object bounding contours. On the other hand, the surfaces of objects (e.g., surface textures) often contain many closed contours, and the unoccluded parts of occluded objects form closed contours. Hence it is uncertain whether closure is a robust cue for object boundary detection under natural conditions.

Unlike a good continuation or proximity mechanism, which could be based on local image properties, a closure mechanism must be relatively global in character. Presumably, it would contribute to the formation of extended closed contours by linking together initial groups formed by local good continuation and proximity mechanisms. To be useful such a closure mechanism would have to link together initial groups that would not otherwise be grouped by good continuation and proximity alone. For example, a closure mechanism might help bridge large gaps in contours due to occlusion, edge orientation noise, or spurious groupings.

A useful method for testing hypotheses about contour grouping mechanisms is to measure contour detection performance in random element displays. With proper randomization it is possible to design stimuli where the detection task can be performed only by grouping along certain stimulus dimensions. This allows one to rigorously test models by manipulating those dimensions in isolation. Using such displays, a large number of studies have investigated the role of good continuation in contour grouping and have provided strong evidence for its importance (e.g., Dakin & Hess, 1998; Feldman, 2001; Field et al., 1993; Geisler et al., 2001; McIlhagga & Mullen, 1996; Pettet et al., 1998).

Fewer studies have examined the effect of closure (Braun, 1999; Elder & Zucker, 1993; Kovacs & Julesz, 1993; Pettet et al., 1998). Kovacs and Julesz (1993) manipulated contour detectablity by varying contour element density and found that closed contours were more reliably detected at smaller element densities than were open contours. Qualitatively similar results were reported by Pettet et al. (1998), who varied the background element density, and by Braun (1999), who varied contour element density. In a different paradigm, a search task, Elder and Zucker (1993) varied the degree of closure and connectedness of targets (line drawings) and found that the greater the degree of closure the shorter the search time. These studies have provided some evidence that closure is important in contour detection; however, a careful consideration of recent contour grouping models, and of the experimental details of previous studies, led us to reexamine the role of closure.

Our first observation is that some of the reported benefits of closure on contour detection may be the result of good continuation and proximity. For example, the rank order of detection performance in Elder and Zucker (1993) and Pettet et al. (1998) is qualitatively consistent with what would be expected from good continuation and proximity. We note, however, that neither of these studies was trying to explicitly distinguish between good continuation and closure, although Pettet et al. do propose a neural mechanism that enhances the salience of closed contours (see later).

Our second observation is that a closure effect might result from statistical factors (probability summation) in conjunction with good continuation and proximity. The argument is as follows. Target contours in random element displays are obscured by false contours, which are created by chance groupings among the background elements. Suppose that on average five contour elements must be grouped in order for a contour to be distinguished from the chance groupings among the background elements. All other things being equal, the probability of obtaining a five-element group will be higher for a closed contour than for an open contour. This is illustrated in Fig. 1 where the "S" and "circle" contours have the same smoothness and the same eccentricity (given fixation on the "plus"). Because the circle is closed there are 16 possible contiguous groups of five, but only 12 for the S. Thus, for simple statistical reasons (probability/information summation) the circle would be expected to be more detectable than the S. Probability summation could have contributed to all the previously reported effects of closure.

The third observation is that previous studies did not fully control for stimulus uncertainty. It is well known

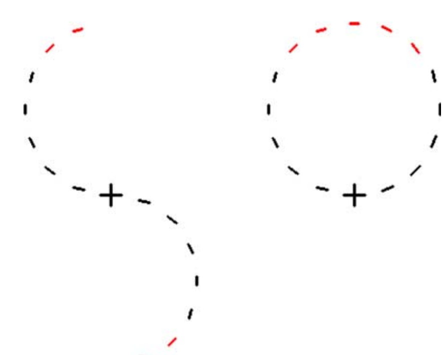

Fig. 1. Illustration of the probability summation advantage for closed contours in a contour detection task. Suppose that on average five contour elements must be grouped in order for a contour to be distinguished from the chance groupings among the background elements. In the S, the five contour elements shown in red have a large break in the middle. The corresponding five contour elements on the circle are contiguous, demonstrating how the circle has more contiguous groups of five elements than the S, making it more likely that the circle is detected. (For interpretation of the references in colour in this figure legend, the reader is referred to the web version of this article.)

that the greater the stimulus uncertainty (in space, time, shape or luminance) the more difficult the task. In Kovacs and Julesz (1993) the closed contours were more constrained in shape than the open contours; this difference in shape uncertainty may have contributed to the observed closure effect. Similarly, in Braun (1999) the closed contours were more constrained than the open contours: the set of open contours was created from a smaller set of closed contours "...by 'cutting' a closed contour at a random location and by 'flipping' (i.e., changing the sign of) the joint angle between the third and fourth element on either side of the 'cut'." The difference in uncertainty for closed and open contours was probably not as great as in Kovacs and Julesz, but the observed closure effect was also smaller.

The fourth observation is that previous studies did not fully control for eccentricity effects and element density artifacts. To compare detectability of closed and open contours it is important to ensure that the eccentricities of the individual contour elements are the same for both conditions. It is also important to ensure that contour and background element density is the same for both conditions, so that differences in detection performance are not produced by differences in local contrast or luminance.

Given these observations we attempted to design experiments measuring detection performance for closed and open contours, where uncertainty effects, eccentricity effects, and element density were held constant. Once these factors are controlled, an observed closure effect could be due either to a closure mechanism, to probability summation, or to both. Thus, to conclude that there is a closure mechanism one must obtain a closure effect greater than that expected from probability summation alone. We estimated the closure effect expected from probability summation alone by generating predictions for a simple good-continuation model derived from natural scene statistics (Geisler et al., 2001).

2. Methods

Detection performance for closed and open contours was measured using a two interval two-alternative forced choice procedure, where stimuli were presented briefly enough to prevent eye movements. There were five separate contour detection experiments. In this section we present the general methods common to the experiments. Details unique to particular experiments are presented in the results section.

2.1. Stimuli and procedure

As illustrated in Fig. 1, target contours were either a circle of diameter 2.5° (closed contour) or an 'S' made of two half circles of the same diameter (open contour). In this way the geometrical relationships between adjacent contour elements due to the curvature was the same for open and closed contours. Also, there was only one possible shape for open contours and one possible shape for closed contours, equating shape uncertainty. Closed contours were placed so that they passed through the fixation point. Open contours were placed so that the point of connection between the two half circles fell on the fixation point. In this way, the eccentricities of the contour elements were held the same for both types of contours. Finally, on each trial, the contours were rotated randomly about the fixation point, equating location uncertainty.

Target contours were embedded in a background of line elements placed at random locations and orientations within a circular display region (see Fig. 2). The density of both the contour and background elements was fixed at 6.8 elements/deg^2; 16 elements in the target and 272 elements in the background. Elements were 1×10 pixels ($0.015\times0.15°$) and were placed so that their centers were separated by at least 20 pixels (0.31°). The procedure for placing contour and background elements

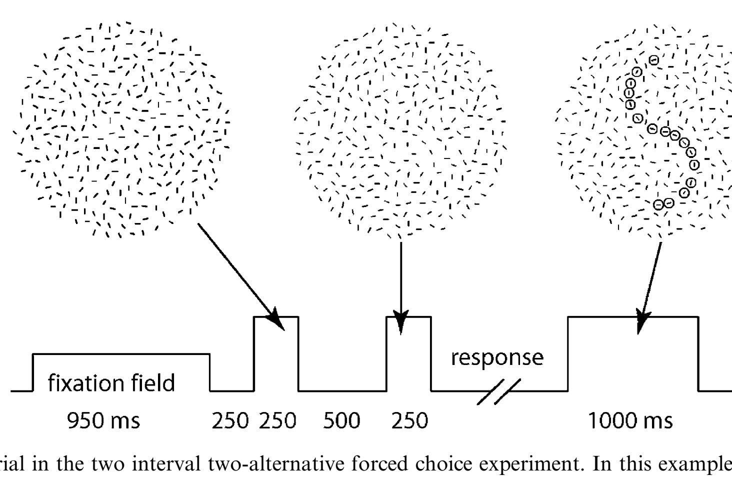

Fig. 2. Time line for a single trial in the two interval two-alternative forced choice experiment. In this example the target contour is in the second interval.

was the same as reported previously (Geisler et al., 2001). Element locations were first selected for the contour and then for the background. To place an element a candidate location was randomly selected. If the candidate location was within the exclusion radius of 20 pixels of any previously selected element, it was discarded; otherwise, it was added to the set of elements in the display. This process of choosing element locations was repeated until the desired element density was reached. The orientations of the background elements were random (0–180°). The orientations of the contour elements were first aligned with the contour and then randomly jittered with a uniform distribution over some given range (100% jitter corresponding to ±90°).

On each trial the subject viewed a baseline image and an image with an embedded target contour (see Fig. 2). The baseline image was generated in exactly the same way as the target image, but the line elements of the 'embedded contour' were randomly oriented (100% jitter). The elements of the baseline and the target images were generated independently, and the temporal order of the two images was random from trial to trial. After viewing the two images, the subject indicated with a button press which interval contained the target contour. The subject was then presented with a feedback image showing the location of the target contour line elements. A tone was played if the subject responded incorrectly. Subjects viewed the monitor using a chin rest at a distance of 220 cm from the screen in a dark room. The monitor was monochrome (Vision Research Graphics M21L-67S01), and was calibrated using a photodiode (PIN-10 United Detector Technologies) and a spectroradiometer (Photo Research Spectra Scan 704). The circular display region was 7.4° across, and had an average luminance of 82 cd/m^2 for Experiments 1–3 and 68 cd/m^2 for Experiments 4 and 5. The chromaticity coordinates of the phosphor were $x=0.396$ and $y=0.522$. Two of the authors (TT and WG) served as subjects.

A single experimental session consisted of 16 blocks of 30 trials. Open contour conditions were run in increasing order of difficulty and then again in decreasing order of difficulty. Then, the same was done for the closed contour conditions. To control for practice effects, a second session was run with the order of the open and closed contour conditions reversed.

2.2. Contour grouping model

Subjects' performance in the experiments was compared with the predictions of a contour grouping model based on natural scene statistics (Geisler et al., 2001). The local grouping rule used in the model was generated by measuring the statistics of the pairwise geometrical relationships between contour elements in images of natural scenes. As shown in Fig. 3A the geometrical relationship between any two contour elements can be characterized by three parameters: the distance between the contour elements, d; the direction of the second element relative to the orientation of the first, ϕ; and the orientation difference between the two contour elements θ. To measure the pair-wise statistics, edge elements were extracted by an automatic algorithm from natural images and human observers assigned edge elements to physical contours (see Geisler et al., 2001). From these assignments one can compute the probability of each possible geometrical relationship for edge elements belonging to the same contour, $p(d,\phi,\theta|c)$, and for edge elements belonging to different contours, $p(d,\phi,\theta|{\sim}c)$. The ratio of these two probabilities gives the likelihood that the edge elements (with the given geometrical relationship) belong to the same contour.

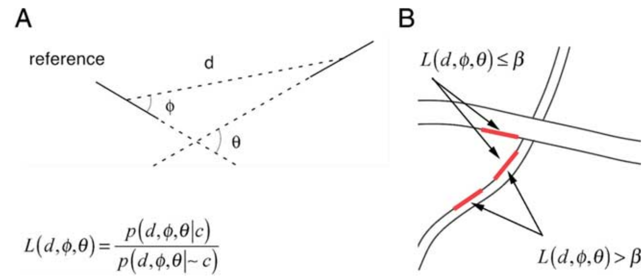

Fig. 3. Model of contour grouping based on natural scene statistics. (A) The geometrical relationship between any two edge elements can be characterized by three parameters: the distance between the edge elements, d; the direction of the second element relative to the orientation of the first, ϕ; and the orientation difference between the two edge elements, θ. Once human observers have grouped edge elements into contours, the conditional probabilities of a particular geometrical relationship can be computed (conditional on the two edges being part of the same contour, or being from different contours). The likelihood that two edges belong to the same contour can be computed from these conditional probabilities. (B) If the likelihood ratio of a pair of elements exceeds the criterion, β, then the two elements are grouped.

In the model, we assume that if the likelihood ratio exceeds a criterion, β, then the pair of elements is grouped (see Fig. 3B). After the pair-wise groups are formed, the groups that overlap (i.e., share elements) are combined, using a simple transitive grouping rule (Geisler & Super, 2000): if edge a groups with edge b and b groups with c, then a groups with c. On each trial, these combined groups are computed for each stimulus interval, and the interval containing the group with the greatest number of elements is picked (see Fig. 4). (In computing the size of a group, edge elements are not counted if they are located near the edge of the display where target edge elements cannot appear.) In generating predictions, the model takes as input exactly the same set of images presented to the human observers. The only free parameter in the model is the criterion, β, which is set to maximize the model's overall performance on the task.

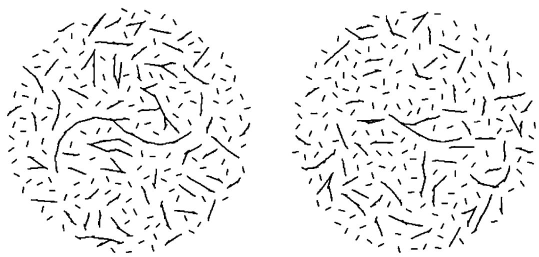

Fig. 4. Groups created by the model from a target image (left) and a baseline image (right). In this case, the model observer would pick the image on the left as containing the contour, because it contains the group with the largest number of contour elements.

3. Results

In our first experiment, line elements were placed at random locations along the target contour, with the restriction that their centers were separated by at least 20 pixels (e.g., the stimuli in Fig. 2 were generated in this fashion). Psychometric functions were measured by varying the amount of orientation jitter of the contour line elements. The data for two subjects are shown in Fig. 5. As can be seen, the subjects showed little difference in performance for open vs. closed contours under these conditions (the 95% confidence intervals overlap at each level of orientation jitter). Interestingly, the model predicted no difference.

One possible explanation for the lack of a closure effect is that the random sampling of line elements along the contour (the jitter in spacing) created breaks that were too large for the closure mechanism to overcome. We attempted to test this hypothesis in a second experiment by placing the line elements uniformly along the contour (e.g., see the stimuli in Fig. 1). As shown in Fig. 6, the results and the predictions of the model are qualitatively similar to those of the first experiment.

It may seem surprising at first that the model does not predict a closure effect due to probability summation (as

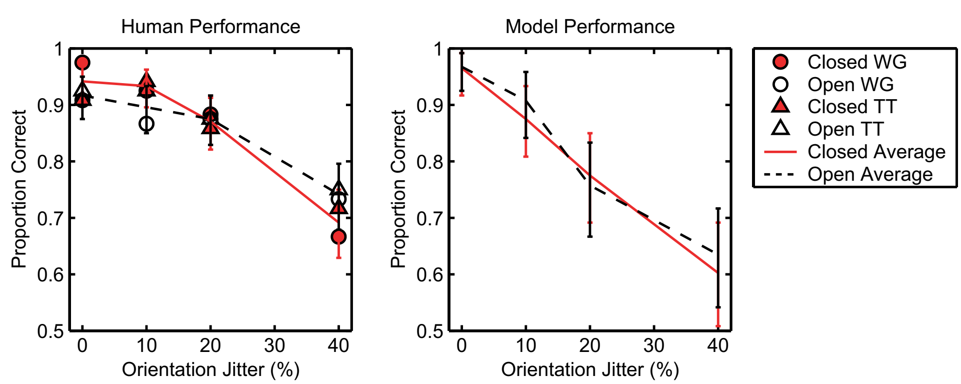

Fig. 5. Contour detection accuracy as a function of the orientation jitter of the target contour elements. The target elements were located randomly along the contour. Each data point represents 120 trials. The differences in performance between the closed and open conditions are not significant for either TT ($\chi^2 = 0.97$, $p > 0.9$) or WG ($\chi^2 = 8.67$, $p > 0.05$). The model also predicted no difference in performance. In this and all subsequent graphs, the error bars are the 95% confidence intervals based on the binomial probability distribution. The error bars for the average human performance are based on 240 trials per point (the total for both observers). The error bars for the model performance are based on 120 trials per point.

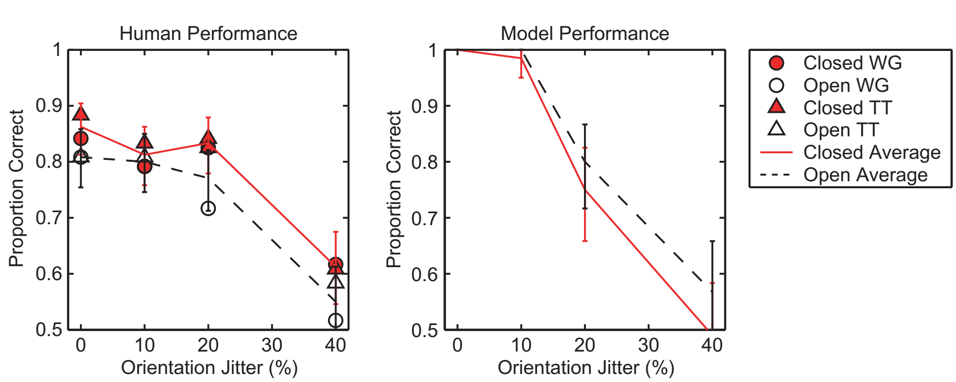

Fig. 6. Contour detection accuracy as a function of the orientation jitter of the target contour elements. The target elements were located uniformly along the contour. Each data point represents 120 trials. The results are qualitatively the same as in the previous experiment. The differences in performance between the closed and open conditions are not significant for either TT ($\chi^2 = 3.14$, $p > 0.5$) or WG ($\chi^2 = 6.93$, $p > 0.1$). The model also predicted no difference in performance. The error bars for the average human performance are based on 240 trials per point. The error bars for the model performance are based on 120 trials per point.

mentioned in the introduction). However, the model's behavior can be understood by considering the effect of orientation jitter on probability summation. As the level of jitter increases the average size of the groups of contour elements gets smaller. For small groups, the statistical advantage for closed contours from probability summation is small. On the other hand, with a low level of jitter the groups are larger, and the effect of probability summation will be larger. But, in this case the performance is at ceiling for both open and closed contours.

In our third experiment, we modified the stimuli so that the model predicted a difference in detectability of closed and open contours. Instead of having only randomly oriented line elements in the baseline image, we embedded a partial contour in the baseline image (see Fig. 7). The partial contour was a partial circle for the closed condition and a partial 'S' for the open condition. The partial contour was oriented randomly and independent of the orientation of the target contour. The partial contour always passed through the fixation point (like the target contour), and the line elements that were eliminated (i.e., were given random orientations) were always those furthest from the fixation point. We fixed the orientation jitter of the contour elements to zero (but included the jitter in spacing), and measured detection performance as a function of the length of the baseline contour. We reasoned that this should cause a reduction in model performance, while allowing the good continuation and proximity mechanisms to create relatively large groups of contour elements. As a result, the ceiling effect that we saw in the last experiment should be reduced without reducing the closure effect due to probability summation. As shown in Fig. 8, the model now predicts an effect of closure and the human observers show an effect of similar magnitude. (Note that the model still shows some ceiling effect at the two shortest baseline contour lengths.)

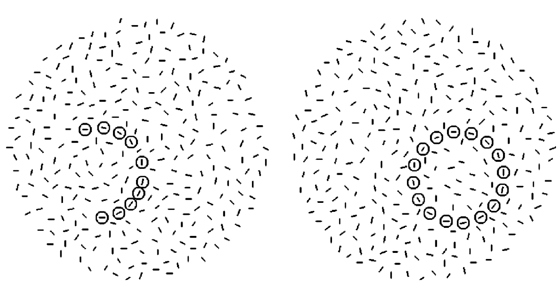

Fig. 7. Partial contour baseline image (left) and target image (right) for the closed condition (for clarity, contour line elements are circled). For the open condition, the baseline image contained a partial 'S' and the target a full 'S'. Subjects were asked to pick the interval with the target image.

In the three experiments described so far, we did not observe an effect of closure beyond that explained by probability summation. In the fourth and fifth experiments, we explored the possibility that closure effects may occur in simpler contrast detection tasks. In these experiments we eliminated the background elements and measured contrast detection performance for closed and open contours. In both experiments the contour elements were uniformly spaced. In the fourth experiment, we measured contrast psychometric functions, with all the line elements in a display having the same contrast relative to the background. In the fifth experiment, we attempted to compensate for differences in sensitivity with eccentricity. In a preliminary experiment we measured detection thresholds for the target element at several eccentricities (data not shown here).

These thresholds were fitted with the function, $c(e)=c_0(e_2+e)/e_2$, where c_0 is contrast threshold at zero eccentricity; e is eccentricity; and e_2 is a free parameter. This function, which has been found to describe changes in sensitivity with eccentricity (Wilson, Levi, Maffei, Rovamo, & DeValois, 1990), accounted for 98% of the variance in the thresholds in both subjects, with param-

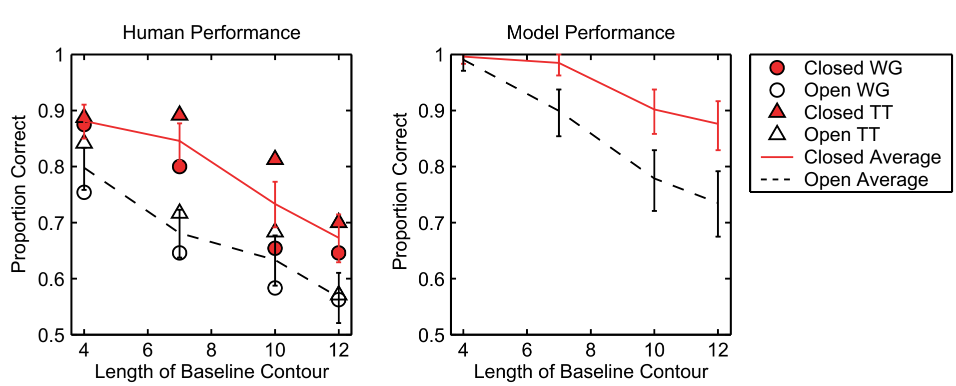

Fig. 8. Contour detection accuracy as a function of number of elements in the baseline contour image (see Fig. 7). Each data point represents 240 trials. The differences in performance between the closed and open conditions are highly significant for observers TT ($\chi^2=45.6$, $p<0.001$) and WG ($\chi^2=32.2$, $p<0.001$). Note that there are more trials in this experiment than in the previous two experiments, however, the differences are still highly significant when only 120 trials are analyzed. The model predicted better performance for closed contours because of probability summation (see Fig. 1). The error bars for the average human performance are based on 480 trials. The error bars for the model are based on 240 trials.

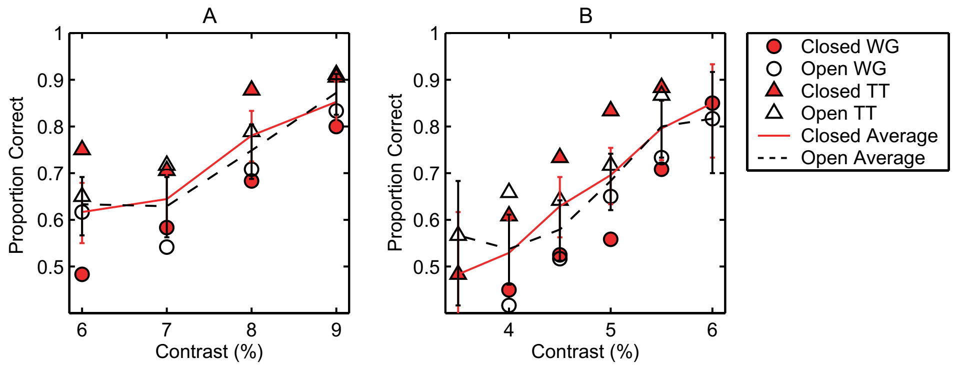

Fig. 9. Detection accuracy as a function of target contrast in displays without background elements. (A) Contour elements had the same contrast, independent of eccentricity. Each data point represents 120 trials. The differences in performance between the closed and open conditions are not significant for either TT ($\chi^2 = 6.37$, $p > 0.1$) or WG ($\chi^2 = 5.37$, $p > 0.2$). The error bars for the averages are based on 240 trials. (B) Contour elements were adjusted in contrast to be approximately equally detectable at all eccentricities. In this panel, the abscissa indicates the contrast at zero eccentricity. Because this experiment was run over different ranges of contrasts, the number of trials differs for each condition. There were 60 trials for each data point in the 3.5% and 6% contrast conditions, 90 trials for the 4% and 5.5% contrast conditions, and 120 trials for the 4.5% and 5% contrast conditions. The differences in performance between the closed and open conditions are not significant for either TT ($\chi^2 = 8.64$, $p > 0.05$) or WG ($\chi^2 = 2.69$, $p > 0.6$). Error bars for the averages are based on the total number of trials for each condition for both observers. (Note that there was only one observer for the 3.5% and 6% contrast conditions).

eter values $c_0 = 7.6\%$ and $e_2 = 1.8°$. Using this value of e_2, the contrast of each contour element was scaled according to its eccentricity, by the factor $(e_2 + e)/e_2$. This insured that the each line element was approximately equally detectable. The results for both experiments are shown in Fig. 9. As can be seen, we observed no systematic differences in the detectability of closed and open contours, although there were overall differences in sensitivity for the two observers.

4. Discussion

In an attempt to assess the role of closure in contour grouping, we measured detection performance for closed and open contours in five experiments designed to control for the effects of uncertainty, eccentricity, and element density. The effects of probability summation were assessed by predicting detection performance using a simple model observer with good continuation and proximity mechanisms, but no closure mechanism.

In the first two experiments we varied contour element orientation jitter (with and without spacing jitter) and found no effect of closure. If a closure effect were found in either of these experiments, it would have been good evidence for a closure mechanism, because the model observer showed no closure effect due to probability summation. No effect was predicted because contour noise prevented larger groups of elements from being formed by good continuation plus proximity (when the model observer's performance was below ceiling). These conditions are presumably similar to some that can occur in natural scenes (spacing and/or orientation jitter are common) and hence would be the sorts of conditions where a closure mechanism could conceivably be of some benefit. We note that in Fig. 6 there appears to be a small effect of closure for subject WG, but the effect is not significant even at the 0.1 level. Further, there is no trend for subject TT ($p > 0.5$). Obviously, the possibility remains that a closure effect would be found if a sufficiently large number of trials were run; however, if the effect exists, it is likely to be small, unlike the effects reported in previous studies.

In the third experiment, the task was to discriminate complete from partially complete contours. The contour elements had no orientation jitter, but still had spacing jitter (as in the first experiment). Under these conditions we found a substantial effect of closure. For the human observers to discriminate open contours with the same reliability as closed contours, the length of the partially complete contours had to be reduced by approximately a factor of two (see Fig. 8). However, the magnitude of the closure effect expected from probability summation was also quite large and in approximate agreement with the measured effect. For closed contours the model observer is approximately 87% correct when the length of the baseline contour is 12 elements. To achieve the same performance on open contours the baseline contour must be reduced in length by approximately a factor of two (see Fig. 8). This substantial effect of probability summation could be one of the important factors explaining the better performance for closed contours reported in previous studies. In general, whenever the stimulus conditions are such that a large fraction of the elements are being grouped on each trial (by good continuation plus proximity), then probability summation will produce a substantial improvement in performance for closed contours.

In the fourth and fifth experiments we measured contour detection performance, as a function of contrast, in uniform backgrounds (no background elements), without and with compensation for the variation in contrast sensitivity of the contour elements with eccentricity. Again, we found not effect of closure.

The fact that we found no clear effect of closure either in cluttered or uncluttered (uniform) backgrounds under several different conditions suggests that the lack of a closure effect may be quite general. However, we have not explored all possibilities. For example, in the first two experiments, if the contrast of the line segments was increased as a function of eccentricity (as in Experiment 5) would there be an effect of closure? This is unlikely for two reasons. First, Experiment 5 showed no effect of closure (see Fig. 9B). Second, Experiment 3 clearly demonstrated that observers are able to detect and make use of the contour elements in the periphery. As can be seen in Fig. 8A subjects were able to discriminate (well above chance) a fully closed contour with sixteen elements from one with the four most eccentric elements randomized in orientation.

Also, in our experiments the target contour was constrained to pass through the center of the display (although due to the random placement of line elements, there was not always a line element at the center). Previous studies generally had greater positional uncertainty for the target contour. Might higher levels of target uncertainty produce a greater effect of closure? This does not seem likely given that there was still a substantial level of uncertainty in the present study: the target contour was located in a random direction around the fixation point, the target and background elements were randomly placed, and the target and background elements were randomly jittered in orientation. In addition, it is hard to imagine what kind of plausible closure mechanism would sharply "switch on" to an incremental increase in uncertainty.

Some models of contour grouping (which have been used in predicting the results of contour detection experiments) hypothesize the existence of neural mechanisms (e.g., reverberating circuits) that enhance the salience of grouped elements, if they form a closed loop (e.g., Pettet et al., 1998; Yen & Finkel, 1998). The results of the present study suggest that these sorts of mechanisms are not necessary to account for the effects of closure on contour detectability. Instead, we find that the effects can be accounted for (at least qualitatively) by a simple model based on the pair-wise edge statistics of natural images, plus a transitive grouping rule. Our model is surely too simple, but its shortcomings are more likely due to an unsophisticated mechanism for good continuation than to the absence of a closure mechanism.

Although our study provides no evidence for low-level closure mechanisms, it is possible that closure mechanisms play an important role in perceptual organization. Consider the Gestalt-type demonstration in Fig. 10. In A, the dominant interpretation is of two crossing lines (two 'sticks') or maybe two touching 'pencil points'; in B, the dominant interpretation is of two closed, touching objects (two 'butterfly wings'). The crossing lines are identical in A and B, but closing the contours in B clearly influences the interpretation. This kind of effect is not inconsistent with the results of our experiments. The demonstration in Fig. 10 shows that closure may affect the interpretation of contours, but this demonstration should not lead one to expect an effect of closure on detection in random element displays. For example, in performing a detection task, an observer might compare all possible groupings of elements to a template of the target. Each grouping of elements could be perceptually organized (interpreted) in different ways (that may be influenced by closure), but as long as each grouping of elements is faithfully compared with the template, the performance in the detection task will be the same.

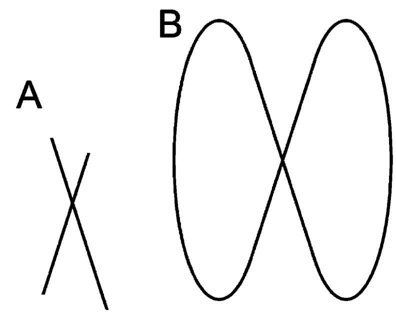

Fig. 10. Typical demonstration of the effect of closure in perceptual organization (see, for example, Wertheimer, 1958). Although (A) is a strict subset of (B), our interpretation of the same set of lines tends to change as a result of the closure, showing that closure can affect perceptual organization.

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