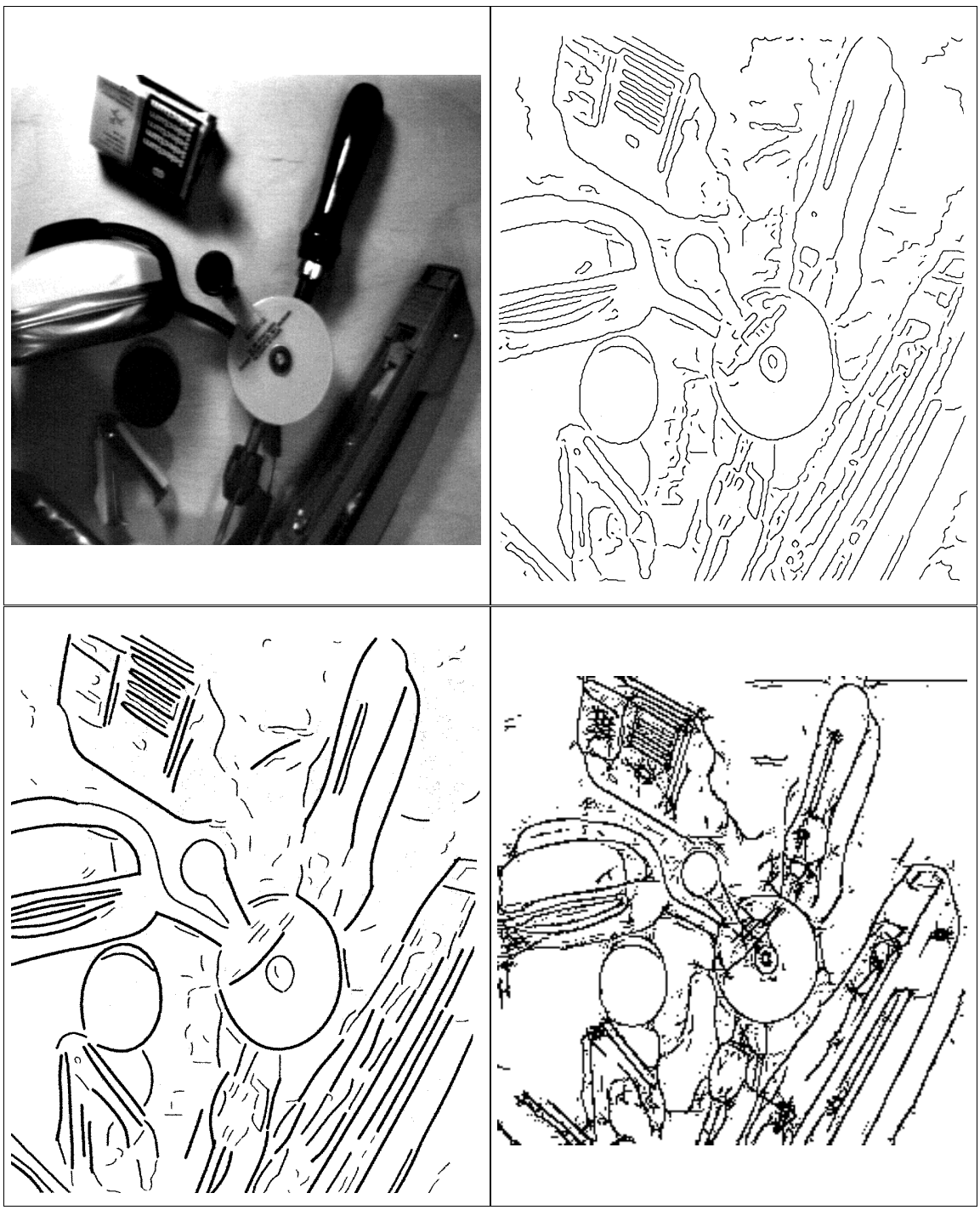


Figure 6: The arrangement of the images is the same as in Figure 5.

5 Experimental Comparison with Psychological Data

Beck et. al. [BRI90] conducted a set of psychophysical experiments to investigate preattentive detection of lines composed of discrete elements. In each trial a horizontal or vertical line composed of disconnected elements was presented in the center of the display for a brief period of time (150 or 300 msec) in a background of a randomly generated pattern of distractors. The subjects' task was to detect whether the line was horizontal or vertical. Mean reaction time and mean total errors across subjects are presented for each experiment. We only compare the predictions of our algorithm with the total mean error data.

The stimuli from experiment 1 in their paper was used to compare the predictions of our model with the psychophysical data. The elements in the stimuli for this experiment were either bars or blobs with three possible aspect ratios, and whose principal axis (for aspect ratio different than 1) was either collinear with the orientation of the line orthogonal to it, making for a total of ten stimuli that are shown in Figure 7. In all stimuli, two fixed values were used for the distance between the elements making the line and the minimum possible separation between distractors. The resulting mean total error from their experiment is plotted in Figure 8a.

To compare prediction from our model with the results from this experiment, we generated the ten images in Figure 7. The distance between elements on the line, the minimum distance between distractors, and the dimensions of bars are as quoted by Beck et. al., and the blobs were reproduced from Figure 2 of their paper. The images were scaled down in half using low-pass filtering. For each of the resulting images we computed $C(x, y, 0°, 0)$, and $C(x, y, 90°, 0)$ using σ of 6.5 pixels.

To measure the errors predicted by our algorithm we used the negative of the ratio of the total response in the central vertical strip of $C(x, y, 90°, 0)$ to the total response in the central horizontal strip of $C(x, y, 0°, 0)$. The strips were 8 pixels wide. The resulting predictions are plotted in Figures 8b. Note, that the algorithm predicts the trend evident from the psychophysical data, where the lines made of collinear blobs or bars are detected more reliably then lines made of orthogonal elements.

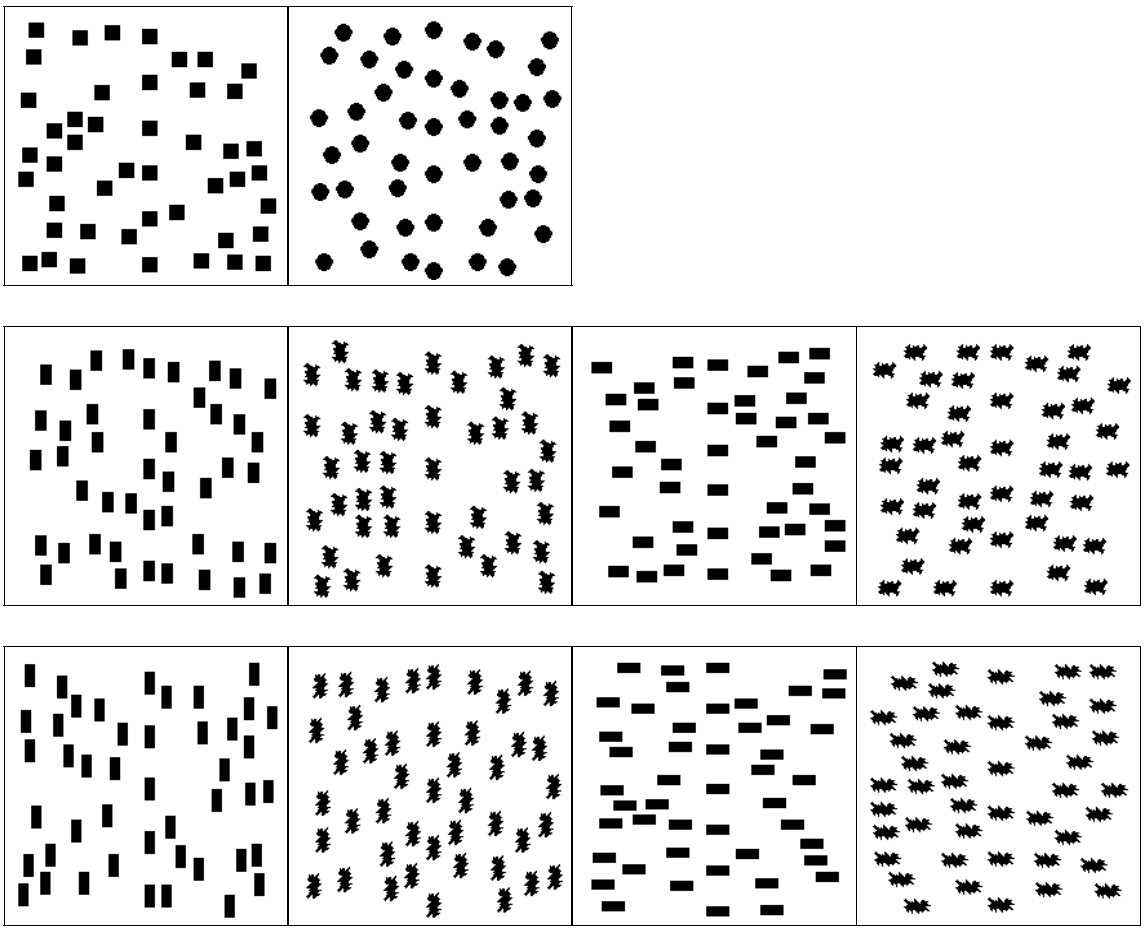
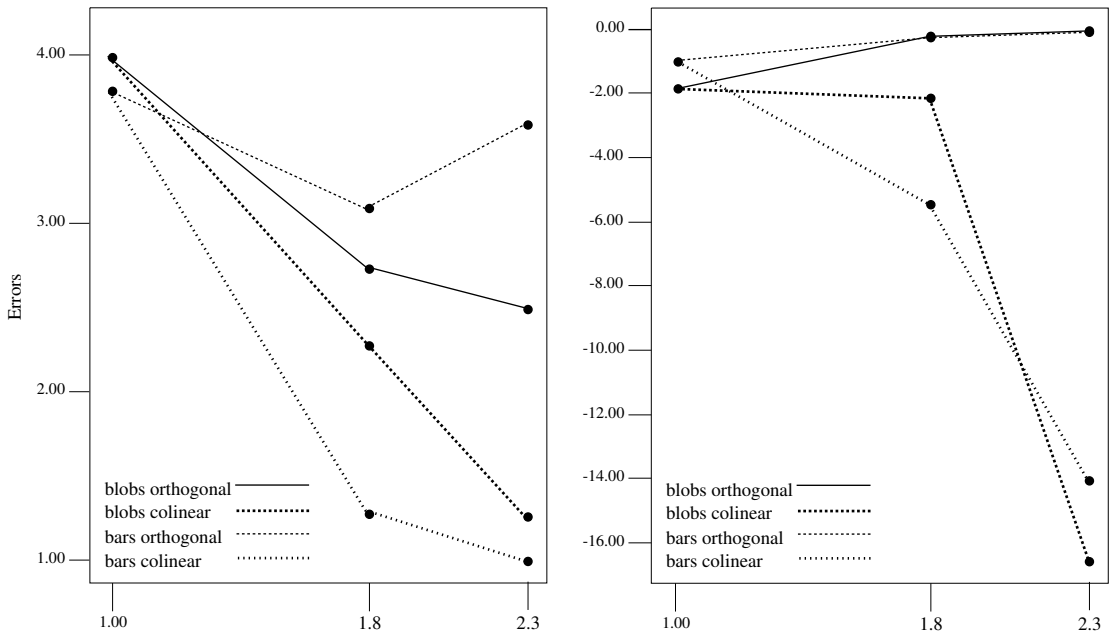


Figure 7: The stimuli for experiment 1. The target line is vertical. In the first and second columns are the collinear bars and blobs, respectively. In the third and forth columns are the corresponding orthogonal elements. Aspect ratios are, from top to bottom, 1,1.8, and 2.3.



a. Mean total errors in experiment 1 (Reproduced from [BRI90]).

b. The predictions of our algorithm.

Figure 8: The psychophysical data and the experimental predictions of our scheme. Smaller numbers along the Y axis represent improved performance.

6 Discussion

The reader may be interested in a comparison of our scheme with the other approaches. Our scheme is extremely simple – it places curvilinear grouping squarely in the domain of low-level filtering type operations. We believe that its simplicity and speed make it dominate over the Parent and Zucker approach which is probably similar in performance – though we have not yet carried out detailed comparative experiments. Parent and Zucker are to be credited with originating the idea of curvature consistency – we exploit the idea in a much simpler way. The Sha'shua and Ullman approach uses many more iterations. Again a comparative empirical study would be worthwhile to determine its performance.

Our scheme is non-iterative and therefore lends itself to a completely parallel implementation. Its feed-forward nature also makes it a plausible biological model for preattentive curvilinear grouping in the human visual system. The preliminary comparison of the predications of the model with psycho-physical data seems to reaffirm this claim. Further comparisons are needed to test the predictions of our scheme against other psychological evidence.

An important issue that is not fully addressed by our current scheme is the combination of curvilinear groupings at different scales. While we address the combination of grouping at different curvatures, the combination of groupings formed at different distance scales (different values of the distance attenuation parameter σ in Equation 2), and at different σ_1, and σ_2 values of the linear filters producing the response image $L(x, y, \theta)$ is not addressed. Clearly these are issues that need to be addressed if one is to extend this scheme to explain scale invariant grouping, and the detection of curvilinear structure at multiple scales.

The selection of the appropriate response image $L(x, y, \theta)$ is another issue that is important both from the theoretical and practical points of view. While the combined response image $V(x, y, \theta)$ provides for the detection of both bars and edges, and for the correct localization of composite edges, its signal to noise ratio is about 50% worse then that of the either odd or even response images for a pure odd or even stimulus. Another problem is that the even-symmetric filters produce strong response to uniform textures. While this response can be suppressed at the non-maxima suppression stage of a linear filtering scheme, in our scheme, when the support of the arc detector is large, and the texture contains enough curvilinear structure, spurious local spatial maxima might be created. This phenomena was quite significant for the case of the totem pole

(Figure 5) in which the graininess of the initial image shows up as uniform texture in the background. Given a priori knowledge of the type of the significant image boundaries, one can manually select the appropriate response image. It is clear however that an automated (probably local) procedure for selecting the appropriate response image is needed.

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