(4) Since edge detectors often fail to extract the entire occluding boundary, we need to fill in the gaps between the detected occluding boundaries. As this curve inference problem is essentially identical to the surface inference problem addressed in the previous phase, we apply a similar 2-D tensor voting process to extract the occluding boundaries.

(5) Spurious surface regions are then identified and removed from the inferred surfaces.

Figure 5.7(e) presents the description we obtain for the stereo pair shown in figure 5.7(a). A texture mapped view of the inferred surfaces is also shown.
Note that only hangovers next to occluding boundaries are considered spurious. We argue that while the expanded regions of the occluded surface are not supported directly by any binocular evidence, their presence does not violate the uniqueness constraint (as they are occluded). In fact, according to the continuity constraint, their presence is strongly supported by the non-occluded regions of the corresponding surfaces. We hence retain these regions in our output for further analysis using higher level information.

5.2.6 Experimental Results

Shown in figure 5.11 are four examples of shape inference from random dot stereograms. Figure 5.11(a) illustrates the description we obtained for the classical scene of 3 overlapping planes. Unlike the “wedding cake” description obtained by most approaches, our inferred description is that of 3 overlapping planes with holes where the continuity constraint is not strong enough to provide evidence. Note that the system does not infer the presence of a hole, but rather a lack of reliable evidence to infer any surface. Applying the region inference process on the correspondence data, we accurately located the boundaries and the corners of the overlapping planes. Similar results are obtained for the random dot stereogram shown in figure 5.11(b), in which a cross and a square are floating. Depicted in figure 5.11(c) is the cube scene in [36], where junction curves are correctly inferred. Figure 5.11(d) show an interesting case where each white dot in the right image can match to two dots in the left image, producing the effect of transparent surfaces. The images are similar to those in [53].

Shown in figure 5.12 are the results on the Renault part scene. Illustrated in the shaded view of the scene description is the inferred region for the half-occluded background (compare to the correspondence data). A rectified, texture mapped view of the
(a) a random dot stereogram of 3 planes

(b) a random dot stereogram of a cross on top of a smaller square

*Figure 5.11 Experimental results on synthetic data*
(c) a random dot stereogram of a cube

(d) a random-dot stereogram of transparent surfaces

*Figure 5.11 (continued) Experimental results on synthetic data*
scene is also presented. Notice that the left side of the Renault part, which is mostly occluded, is correctly inferred. In both texture mapped views, inferred regions with no texture information are given random texture.

We also applied our algorithm to a building scene captured by aerial image pair, depicted in figure 5.13. Using the knowledge that the target object is block-like building, we combine edge information with the inferred overlapping roof surfaces to derive vertical surfaces that are visible in both images. Inference of vertical surfaces is hard as they are often half occluded, or difficult to obtain by local correlation measurements. Also note that surfaces that are too small to provide correct correspondence are not detected.

5.3 Shape from Shading

Among all image cues, shading is the one that is often available but is the hardest to use. One reason is that the mathematical analysis of the general problem is highly complex. The problem only becomes tractable if a number of simplifying assumptions are made.

We refer the reader to [39] for a thorough study of the general problem. Two main classes of algorithms for computing shape from a shaded image are used: global methods use variational calculus techniques to compute the shape by iteratively minimizing some cost function involving global constraints such as smoothness; local methods use local constraints, such as the assumption that surface is locally spherical or cylindrical, to recover the shape. Both approaches provide numerical solutions to the shape inference problem.
Figure 5.12 The Renault Part Scene

(a) input images

(c) initial point correspondences

(c) unique disparity assignment

*Figure 5.12 The Renault Part Scene*