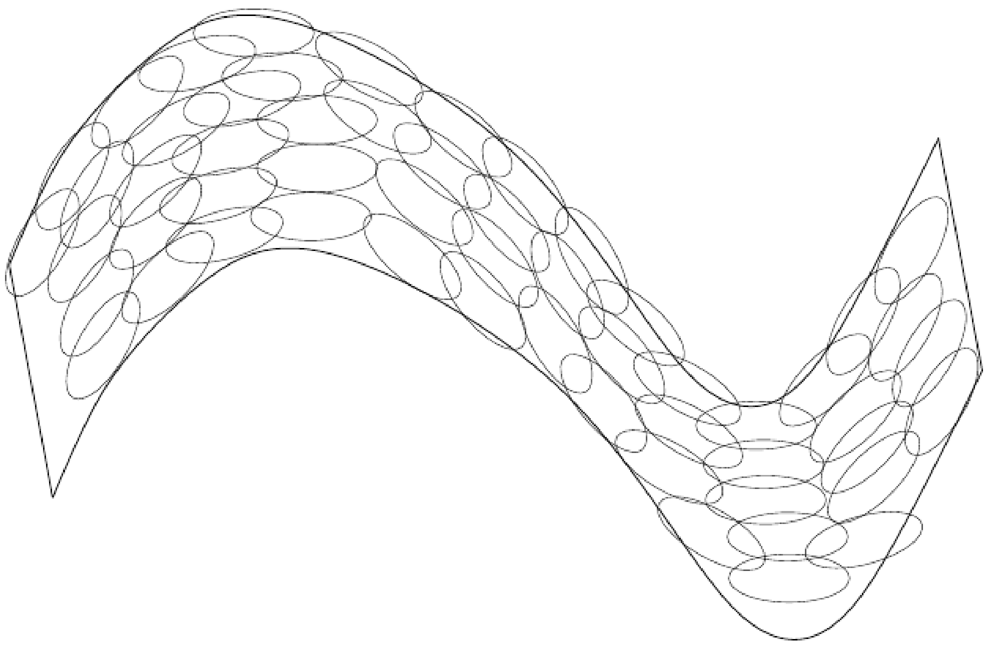

Figure 14.9: If the tangent planes (see figure 14.6) at each location are known, then they can be tiled to form a global coordinate system or a density function. Each local patch can be thought of as a local Euclidean coordinate system or as a locally flat Gaussian, or "pancake," with a very small variance in the directions orthogonal to the pancake and a very large variance in the directions defining the coordinate system on the pancake. A mixture of these Gaussians provides an estimated density function, as in the manifold Parzen window algorithm (Vincent and Bengio, 2003) or its non-local neural-net based variant (Bengio *et al.*, 2006c).

these variations, with no chance to generalize to unseen variations. Indeed, these methods can only generalize the shape of the manifold by interpolating between neighboring examples. Unfortunately, the manifolds involved in AI problems can have very complicated structure that can be difficult to capture from only local interpolation. Consider for example the manifold resulting from translation shown in figure 14.6. If we watch just one coordinate within the input vector, x_i, as the image is translated, we will observe that one coordinate encounters a peak or a trough in its value once for every peak or trough in brightness in the image. In other words, the complexity of the patterns of brightness in an underlying image template drives the complexity of the manifolds that are generated by performing simple image transformations. This motivates the use of distributed representations and deep learning for capturing manifold structure.