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Apparent symmetries in range data

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Abstract: A procedure for extracting symmetrical features from the output of a range scanner is described which is insensitive to sensor noise and robust with respect to object surface complexity. The acquisition of symmetry descriptors for rigid bodies from a range image was in this case motivated by the need to direct pre-grasp configurations in dextrous manipulation systems. However, object symmetries are powerful features for object identification/matching and correspond explicitly to useful geometric object models such as generalized cylinder representations[1].

Key words: Range data, object symmetry.

1. Introduction

Work has been done previously concerning the segmentation of range imagery based on sparse data that relies on surface hypothesis testing [1,4]. These techniques use sparse sets of data to construct hypotheses which are either supported or denied by other such local hypotheses. This approach could conceivably be generalized to identify that class of objects which can be represented by generalized cylinders. The resulting procedure is efficient and may be implemented as a VLSI range image pre-processor. The algorithm described by Lozano-Pérez et al. [4] requires that hypotheses are constructed from a model of the object's surface. The resulting number of competing interpretations of the object derived from such sparse surface measurements, in noisy data, over a large set of object models could prove to be prohibitive. It is in this case that global information concerning the symmetries apparent in the range image can be used to effectively prune the tree of competing interpretations.

Symmetries are a powerful feature in object identification and are also quite useful in applications which require no further surface information. Consider, for example, the problem of selecting initial orientations and approach vectors for a manipulator which has functional symmetries. Knowledge of the principal symmetries of an object and a manipulator are sufficient to prune the set of initial hand/object interaction configurations to an optimal subset. It is in this context that the approach described here was developed.

The procedure has proven useful for identifying symmetrical features within range images. It will, however, produce symmetry parameters (eigenvalues and eigenvectors) for any object and is robust with respect to object orientations. The procedure begins by assigning a normal to each point in the range image from which we identify approximately planar, contiguous segments. This step produces essentially a least squares planar approximation to the object's surface and therefore removes random noise in the sensed data. The planar patch approximation of the object consists of a set of patches each described by centroid, area and normal (directed outward). The centroids are projected backwards along their respective normals to identify positions in space where several such projections converge.

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nar faces. A perfect cylinder, when scanned from a particular set of perspectives, will produce a set of planar patches each of which is a vertical stripe of the cylinder's surface with approximately the same areas and with centroids at roughly the same position along the cylinder's axis. This phenomenon can conceivabley produce too few mass nodes to predict an object's symmetry. The solution to this problem is the definition of a maximum area for contiguous surface elements which creates a new patch if areas grow too large.

The examples presented in this paper were computed without using a maximum area in the planar patches segmentation. To improve the results in those cases where few mass nodes were produced, we lowered the accumulator significance threshold. This permits more data, but unfortunately, data which is less significant.

3. Computing the principal axes

After having identified an object's center of mass and the apparent distribution of mass, a real valued, symmetric inertia matrix, M, can be computed:

$$M = \sum_{i=1}^{n} \omega_i \vec{x}_i^{\mathrm{T}} \vec{x}_i,$$

where
$M =$ a 3×3 inertia matrix for the object,
$\omega_i =$ weight of mass node i, and
$\vec{x}_i =$ world frame position of mass node i.

The principal axes of the apparent mass distribution are just the eigenvectors of the inertia matrix, M. In our experiments we found that a simple iterative method (Jacobi's method) suited our objectives. The magnitude of eigenvalues associated with each of these eigenvectors is proportional to the spread of mass along that particular eigenvector. That is, large magnitude eigenvalues indicate a wide range in the mass distribution along the corresponding axis. If λ_i, λ_j, and λ_k represent the three eigenvalues:

- $\lambda_i, \lambda_j >> \lambda_k \Rightarrow$ a plane whose normal is in the direction defined by the k-th eigenvector,
- $\lambda_i, \lambda_j << \lambda_k \Rightarrow$ an axis defined by the k-th eigenvector, or,
- $\lambda_i \sim \lambda_j \sim \lambda_k \Rightarrow$ spherical symmetry, or two planes of symmetry.

4. Results: Some repesentative examples

Some of the results produced so far by this procedure are presented in the following figures. These demonstrations were all made using the UTAH Range Database [3]. All figures depict the original pointwise data, the mass nodes which satisfy the accumulator significance threshold (the radius is proportional to the *mass*) and the resulting principal axes. The relative magnitude of the eigenvectors associated with these axes are the principal moments of inertia of the object. It is possible, therefore, to identify the dominant type of symmetry: axial, planar or spherical. In the figures, the relative length of the principal axes expresses the apparent symmetry class of the object. Figure 2 illustrates a case where the accumulator threshold indicating the significance of the apparent mass nodes was lowered to include more of them. The lower portion of this surface was represented by tall thin planar patches, whose centroids are prone to error due to the shape of the plane produced in the segmentation. It was not probable that the backcast centroids would intersect. As was mentioned before, the correct solution is to segment the surface into planar patches which do not exceed an area limit. The result will be a roughly uniform segmentation of these large, but somewhat featureless surface regions. The examples presented in Figure 3 did not suffer from a lack of apparent mass nodes and the results are relatively good. Figure 4 demonstrates by the lack of mass nodes near the threaded portion of the light bulb, that the area constraint on the planar patches will undoubtedly improve the results.

The *weight* of the mass nodes shown here are simply the total area of all the patches which contributed to them. Since the accumulator is used to judge the confidence that a node reflects a symmetry in the object, it stands to reason that areas that contribute to a node be roughly equivalent. A node that reflects the intersection of a large and a small surface area may have a significant total area, but may not reflect the correct symmetrical nature of the object. Future versions of this procedure will in-

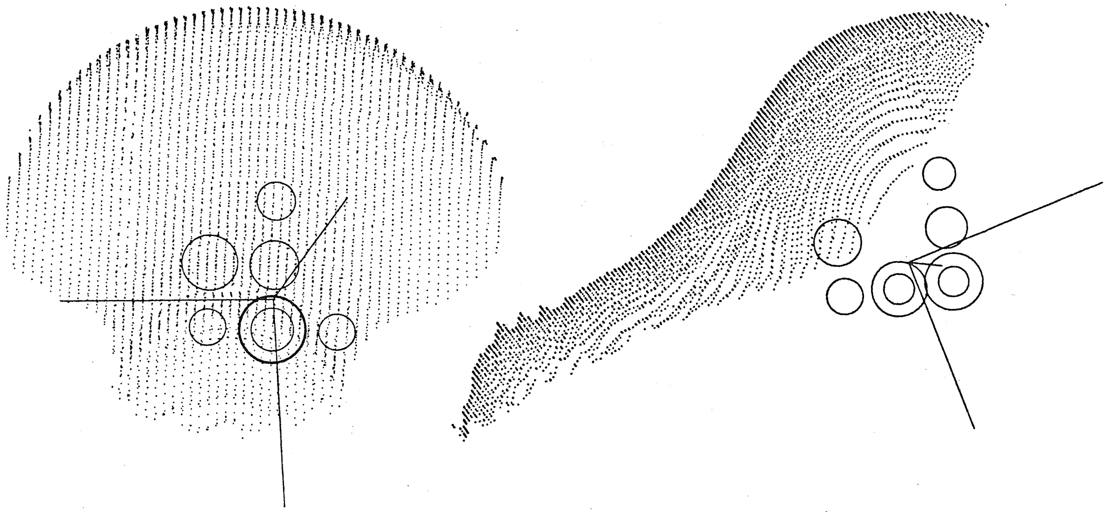

Figure 4. The original 3-space data for a light bulb from two viewing perspectives and the resulting mass nodes (where radius is proportional to mass) and principal axes (where relative length reflects the magnitudes of the eigenvalues).

dure. It is actually more correct to describe the results of this analysis as the apparent principal axes of the object which correspond to the axes of symmetry in symmetrical objects. The program also finds these axes for entirely non-symmetrical, irregular objects and the effectiveness of the procedure to disambiguate these objects is equivalent to its effectiveness for symmetrical objects.

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