UNIFORMITY AND PROXIMITY APPLIED TO THE GENERALISATION OF TARGET FIELDS IN CLOSE RANGE PHOTOGRAMMETRY.

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ABSTRACT:

The design of close range photogrammetric networks can be a difficult task requiring a good understanding of the factors which influence network design and accuracy. The configuration of the network geometry is a critical factor in determining the accuracy which can be achieved for a survey. Expert photogrammetrists draw heavily upon heuristic knowledge and experience throughout this design process. The expert knowledge required has been identified as one of the limiting factors in the application of close range photogrammetric techniques (Mason, 1994). Expert systems offer a means of automating the network design process. Mason (1994) proposed a conceptual framework for network design using an expert system. One of the factors identified in this framework was the need to segment and group the target points into surfaces for which generic camera configurations are known.
This paper builds on work presented by Mason (1994) and Mason and Kepuska (1991), in particular the investigation of whether proximity and uniformity are appropriate criteria for the generalisation of target fields into combinations of planes, cylinders, spheres and cones. Several surface features are reviewed as appropriate indicators of uniformity. The maximum and minimum curvatures and a function of the surface normal coefficients have been selected as the most appropriate uniformity indicators for this evaluation of the uniformity and proximity model. Several different computational procedures which employ uniformity measures to group and/or classify points are reviewed. The paper details the further development of one of these procedures for the generalisation of target fields using uniformity and proximity.

1. NETWORK DESIGN.

1.1 Network Design For Complicated Objects.

The problems to be addressed in the design of photogrammetric surveys were identified by Grafarend (1974) as being four levels of design. This classification of design problems was also adopted by Fraser (1984) and is as follows:

Zero-Order Design (ZOD) : the datum problem.
First-Order Design (FOD) : the configuration problem.
Second-Order Design (SOD) : the weight problem.
Third-Order Design (TOD) : the densification problem.

The nature of the object, physical constraints of the workspace and the limitations of available equipment are critical to the FOD problem and thus the accuracy that can be achieved from the network. The research presented in this paper relates to the automation of the FOD process.

The ten constraints and considerations associated with FOD were dealt with by Mason (1994). These same constraints and considerations were presented by Fraser (1984, 1989), however in these earlier articles they were grouped and treated differently. The ten constraints all limit the placement of sensors (cameras) within the workspace. Several of these network design constraints may conflict (Fraser 1992), and the best compromise is sought when designing an imaging network.

When designing imaging networks for simple objects a formal design process may not be necessary. It is often possible for the photogrammetrist to design an ideal imaging network simply by viewing the object and its survey site. Design by inspection however, requires significant skill and knowledge.

For complicated objects, the network design by simulation process allows for the theoretical precision of object point co-ordinates to be quantified prior to the actual measurement taking place and is virtually mandatory for complex objects (Fraser and Mallison 1992). The simulation process assists the designer in dealing with the many interrelated and competing design considerations of an imaging network required for the survey of a complex object. A limitation of this design by simulation process is that expertise is generally needed to efficiently handle challenging cases (Mason 1994). The requirement for expertise has meant close range analytical photogrammetry has rarely been applied other than by experienced photogrammetrists (Mason 1994).

1.2 Expert Systems For Network Design.

Expert systems are computer systems designed to simulate the problem-solving behaviour of a human who is an expert in a narrow domain (Denning 1986). The design of strong imaging networks (FOD) meets the prerequisites of a task suitable for expert system development (Mason 1994). Expert systems would play an important role in the development of automated network design systems (Mason 1994). The advantage of such an automated system would be to reduce the need for expertise in close range analytical photogrammetric network design, apart from the survey of particularly complicated objects.

In studying the network design strategies of experts, it was identified that they employ heuristic knowledge and appear to use generic networks to overcome the complexity of the sensor station placement task (Mason,1994). A generic network is a known camera configuration providing the best possible survey of all points on a particular surface.

The expert system presented by Mason (1994) is based upon the decomposition of target fields into a number of point groups that relate to the underlying surfaces of the target fields. The target fields are decomposed into combinations of surfaces for which generic camera configurations are known. These generic networks are then combined into a single, strong network for the whole object, giving consideration to the nature of the object, and ensuring the restrictions of the site are accommodated.

The decomposition of target fields into point groups that are representative of the surfaces of the object is the main cognitive operation on which the conceptual model for imaging geometry configuration is based (Mason 1994). Mason was able to suggest a partial model for the grouping of points into the simplest of surfaces for which a generic camera configuration is known: the plane. Points to be grouped as a plane must satisfy two criteria (i) proximity - they must be spatial neighbours; and (ii) uniformity - they must share a similar surface normal (Mason 1994). These criteria are appropriate for grouping points into planar regions, however objects to be surveyed are rarely that simple. Thus, a more general conceptual model for the grouping of points needs to be developed (Mason 1994). The work presented in this paper is part of an investigation to determine the suitability of proximity and uniformity as criteria for grouping points in target fields which lie on surfaces other than planes.

2. UNIFORMITY AND PROXIMITY.

Flynn and Jain (1988) claimed that spheres, cylinders and planes reasonably approximate 85% of manufactured objects. These three surfaces, along with cones, were chosen as the primitive surfaces into which target fields are to be decomposed. The cone was included to increase the range of objects that can be effectively generalised, or alternatively the quality of the generalisations. All four of these surfaces belong to the larger family of quadric surfaces and all can be represented by the expression:

$$F(X, Y, Z) = a_1X^2 + a_2Y^2 + a_3Z^2 + a_4XY + a_5XZ + a_6YZ + a_7X + a_8Y + a_9Z + a_{10} = 0$$

X, Y, Z ~ object co-ordinates.

2.1 Uniformity Indicators.

2.1.1 Indicators Reviewed: The uniformity indicators used for the grouping of points must be applicable to the task of generalising close range photogrammetric target fields. The direction of the surface normal at a point has a bearing on the location of the cameras used to image that point. These surface normal directions indicate the uniformity of a target field. Similar surface normal directions suugest points lie on a near planar surface. Uniformly changing surface normal directions suggest points lie on the same curved surface. The distance between neighbouring points on a surface patch could also indicate the uniformity of points. This indicator is, however, of little value in relation to the intended application. Changes in the spacing between neighbouring points may bear no relation to the orientation of the patch on which they are located. The direction of the surface normal is therefore a potentially useful quantity for the evaluation of target point uniformity.

A review of uniformity indicators used by researchers in the field of computer vision and machine intelligence for the decomposition of complex objects into homogeneous regions identified a number of potentially useful uniformity indicators.

Krishnapuram and Munshi (1991) trialed a number of uniformity indicators in their evaluation of image segmentation techniques. They segmented images using single uniformity indicators and different combinations of two indicators (one related to the surface normal and one related to either the curvature at, or the location of, each point). The five uniformity indicators were:

Orientation angle of surface normal.
Tilt angle of the surface normal.
Gaussian curvature at a point.
Mean curvature at a point.
Euclidean distance of points from an origin.

Krishnapuram and Munshi (1991) concluded that the combination of mean curvature at a point and the orientation angle of the surface normal enabled them to effectively segment images of both planar and curved objects.

Hoffman and Jain (1987) used three uniformity indicators to decompose range images in their three dimensional object recognition system. The uniformity indicators in the minimum justifiable set that could be effectively utilised in their application (Hoffman and Jain 1987) are as follows:

Image co-ordinates (r, c) of points,
Range / depth from sensor ($F(r,c) = z$) of points,
Coefficients of estimated unit surface normal, vector ($A\underline{i} + B\underline{j} + C\underline{k}$) at points.

The use of these three uniformity indicators requires the analysis of six parameters, three for the co-ordinates of each point, and one parameter for each of the three coefficients of the estimated unit surface normal.

The coefficients of a biquadratic facet model :

$$Z_{uv} = B_0 + B_1 u + B_2 v + B_3 u^2 + B_4 uv + B_5 v^2,$$

evaluated for a surface patch about each point were used by Jolion et. al. (1991) as a uniformity indicator in the evaluation of an image segmentation algorithm. As with the uniformity indicators used by Hoffman and Jain (1987), the use of the coefficients of the biquadratic facet model requires the analysis of six parameters.

Flynn and Jain (1988) developed a classification algorithm for the description of segmented range images, using the uniformity indicators of minimum curvature and maximum curvature to discriminate between a sub-set of the quadric surfaces. The minimum and maximum curvatures are evaluated at points known to lie on non-planar surfaces, in order to classify them as lying on spherical, cylindrical, or conical surface patches. Flynn and Jain made use of the known distinctive combinations of these curvature measures in a hierarchical classification process to discriminate between each surface in the sub-set of quadric surfaces.

Surface curvature measures were also used by Besl and Jain (1988) to provide an initial coarse segmentation of range images, to be refined in an iterative region growing process. In this case the values of mean curvature and Gaussian curvature are not used directly, instead a function of the thresholded (-1, 0, +1) values is used to label the surface about a point as being one of eight possible types. Thus, the image is segmented into patches of points with the same or similar surface characteristics, which are then refined.

The algorithms presented by Fan et. al. (1987), Roth and Levine (1993) and Chen (1989) for segmentation and classification of three dimensional objects do not make use of uniformity indicators computed directly from the surface about a point. Instead, they used the residuals of the fit of pre-defined surfaces to indicate the uniformity of points within a patch. These residuals are dependent upon the type of surface being fitted, and the number and distribution of points used in the fitting. Unlike the uniformity indicators used by other researchers, the residuals of a surface fit are not computed in isolation at each point, and are not solely dependent on the surface defined by the points in the target field alone.

2.1.2 Indicators Selected : Of those uniformity indicators reviewed the maximum and minimum surface curvatures and a function of the surface normal coefficients were found to be the most appropriate indicators of point uniformity for the generalisation of target fields. Using indicators related to surface normal and surface curvature simultaneously will enable the decomposition of both planar and curved objects (Krishnapuram and Munshi 1991). The minimum and maximum curvatures were selected over the other measures of curvature, as these two measures have distinctive combinations for points on the quadric surfaces highlighted by the hierarchical classification process presented by Flynn and Jain (1988).

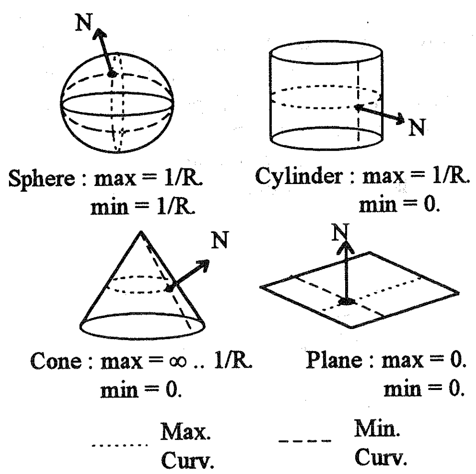

Figure 1. Distinctive combinations of Max. and Min. curvatures for the sub-set of quadric surfaces.

A function of the surface normal has been selected rather than the surface normal itself, as this reduces the number of parameters to be considered at each point. The function of the surface normal coefficients to be used is the orientation (direction) of the surface normal in the object system XY plane. The surface normal at a point is directly related to the direction from which it is to be imaged in network. Using the maximum and minimum curvatures and a function of the surface normal reduces the consideration of uniformity to three parameters at each point as opposed to five if the two curvatures and the coefficients of the surface normal are considered. The excessive number of data elements to be considered at each point is also the justification for rejecting the use of point co-ordinates and coefficients of biquadratic surface approximations as uniformity measures. The use of surface normals and point co-ordinates as uniformity indicators would require the consideration of six data elements for each point, as would the use of the biquadratic surface approximation.

The selected uniformity indicators do not contain any information about the location of points. Thus, if points are grouped based solely on their uniformity indicators, points on disjoint surfaces of the same type will be grouped together. The use of location information (e.g co-ordinates) would ensure that this grouping of points on disjoint surface did not occur, i.e. points would have to be uniform in location. If the issue of disjoint surfaces is not dealt with directly during the grouping of points, then point proximity will have to be established for each group of points created. The requirement for post-processing of point groups is not in conflict with the partial model developed by Mason (1994), which suggested the use of both uniformity and proximity.

2.2 Point Grouping With Uniformity And Proximity.

The algorithms reviewed can be considered as one of three types or a combination of two of these three. Segmentation algorithms partition the data set into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous. Segmentation algorithms do not provide any indication as to the nature of the underlying surface of the point groups. Classification algorithms determine surface parameters or descriptions for the point groups that convey important information about these groups i.e. location and orientation (Flynn and Jain 1988). Neither segmentation nor classification algorithms solve the point grouping problem completely and thus a combination of the two must be used. The third type of algorithms are extraction algorithms that do not have distinct segmentation or classification components. Data sets are not initially decomposed into point groups for which parameters or descriptions are subsequently determined. Instead the total data set is interrogated to identify the presence of surfaces of a predefined type in the data set. Membership of points to these surfaces is then established.

2.3 Algorithms For The Evaluation Of Uniformity And Proximity

A number of algorithms were reviewed and those presented by Jolion et. al. (1991) and Newman et. al. (1993) were selected as being the most suitable for the evaluation of uniformity and proximity as measures to establish target groups.

The clustering algorithm as used by Jolion et. al. can integrate multiple sources of information about the same data set, allowing a more complete analysis (Jolion et. al. 1991). This type of algorithm can also make efficient use of all available uniformity indicators. The algorithms presented by Roth and Levine (1993) and Chen (1989) can only use the fit of points to a geometric primitive and thus the position of points in isolation.

Jolion's algorithm is also 'context-insensitive', unlike Krishnapuram and Munshi's (1991) and Hoffman and Jain's (1987) algorithms. These algorithms require the input of a maximum number of point groups to be formed in the feature space, and thus exhibit the paradox of requiring knowledge about the data set in order to interpret it (Quek et. al. 1993). Jolion's algorithm dynamically selects the appropriate number of point groups in a data driven process.

Jolion's algorithm makes direct use of uniformity indicators without having to threshold them (i.e. map computed values to -1, 0, or +1), as is required for Besl and Jain's (1988) algorithm. Abdelmalek (1990) and Krishnapuram and Munshi (1991) note the difficulty associated with selecting appropriate thresholds for the re-scaling of curvature values.

In addition to using uniformity indicators directly, Jolion's algorithm makes use of the entire data set when producing its decompositions. Errors in the data set do not have significant effects on the results of the segmentation. Other techniques, such as region growing and boundary identification (Krishnapuram and Munshi 1991) or selecting only a small subset of 'significant' data points, may lead to spurious segmentation of the data.

Jolion et. al (1991) have taken an 'intelligent' approach to the target point grouping. The algorithm identifies a portion of the feature space that will produce the most significant cluster, to be refined in a 'brute force' process limited to only a portion of the data set. Krishnapuram and Munshi's (1991) algorithm requires multiple clustering's of the entire data set, from which the best segmentation is selected. This 'brute force' approach to clustering results in a slow and computational inefficient algorithm (Krishnapuram and Munshi 1991).

As indicated earlier the point groups returned from an analysis of the selected uniformity indicators may contain points from more than one surface of the same type. Therefore, a proximity measure must be used to split disjoint surfaces that have been grouped together. To evaluate the proximity of the points, the separation of all points in a group can be computed with respect to one point in the group and in a given direction (Figure 2). The separations from the common point of all points on the same surface will be similar (Figure 2, separations in range $D_1 \rightarrow D_2$). Points on the surface with the same or opposite orientation will have distinctly different separations from the common point (Figure 2, separations in range $D_3 \rightarrow D_4$). The means of these two ranges will be significantly different (Figure 2, $D_{m1} \neq D_{m2}$), indicating that two point groups are not in close proximity. In a majority of cases, the evaluation of point proximity's will separate points on surfaces with the same or opposite orientations. However, the algorithm can not successfully discriminate between points on surfaces if they are parallel and close together, or when the surfaces are duplicated next to each other, as there is no significant difference in the separations of the points.
The descriptions of the point groups created by Jolion's algorithm are to be produced using a modified version of Newman's et. al. (1993) algorithm. The simplicity of this algorithm, its compatibility with Jolion's algorithm and the ease with which it can be modified were significant in its selection as the classification algorithm. The details of this selection process and the evaluation of this algorithm are beyond the scope of this paper.

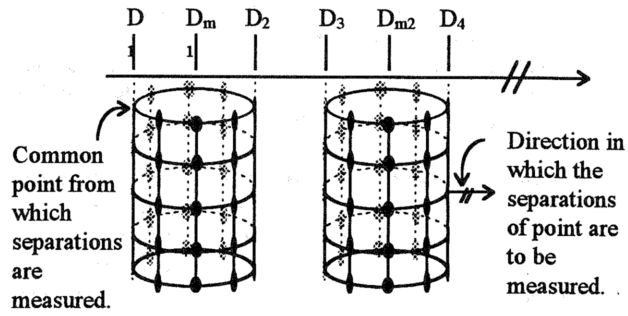

Figure 2. Separation of points for the evaluation of data point proximity.

2.4 Pre-processing Of Target Field Data Sets.

Target fields to be decomposed using the selected segmentation algorithm require pre-processing before the point grouping can be undertaken. The uniformity indicators upon which the point grouping is to be based are computed from the local continuous approximation:

$$w(u,v) = C_1 u^2 + C_2 uv + C_3 v^2 + C_4 u + C_5 v + C_6$$

to the discrete data set of target points. For a majority of cases the surface features can be computed directly from the continuous approximation, however, in the case of points that belong to more than one surface, this is not possible. Direct computation of the surface features from the local continuous approximation would return a single set of uniformity indicators. If the point lies on more than one surface i.e. an edge point, then one complete set of indicators is required for each surface on which the point lies. Figure 3 shows this concept for surface normals at an edge point. Points requiring multiple surface features of each type could be dealt with by creating 'dummy' points. The surface features of each these 'dummy' points relate to the different surface on which the point lies.

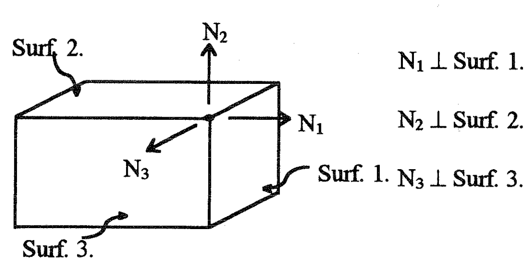

Figure 3. Edge point with multiple valid uniformity indicators.

Points requiring 'dummy' points could be identified by examining the uniformity indicators computed at each point without regard for points being edge points or otherwise, i.e. only one set of indicators for each point. In particular the curvature measures could be analysed to find those points that have curvatures greater than might reasonably be expected at points lying on a smooth surface, indicating that the point lies on a sharp edge.

3. COMPUTER VISION CONCEPTS APPLIED TO PHOTOGRAMMETRIC PROBLEM.

3.1 Nature Of Data Sets.

The algorithms to be evaluated have been successfully applied to computer vision and machine intelligence tasks. A number of difficulties were encountered in developing the algorithms. These were due to the differences between the target field data sets and the data sets used in the computer vision applications. Computer vision data sets are continuous images of only a portion of the object, with an established perspective. The target field data sets are discrete points, representing the entire object. These differences have a significant impact upon the processing strategy to be adopted.

It was intended that surface normal information and curvature information could be considered simultaneously in a three dimensional clustering algorithm as suggested by Krishnapuram and Munshi (1991). However, the problems detailed below have resulted in an alternative processing strategy being adopted.

3.2 Edge Point Identification.

Edge points in the data set need to be given special treatment regardless of the application. In computer vision applications the continuous data sets lend themselves to edge point identification, using well established filtering and simple edge operators (Fan et. al. 1987). The contaminating effects of these edge points on surface feature computation can be reduced or removed by masking out edges in the images.

No simple and effective method was found for identifying edge points in the discrete data sets based upon information that could be computed for each point and its nearest neighbours in isolation. An approach based upon analysis of surface curvatures required the use object dependent thresholds. Furthermore, this approach was not considered to be reliable. Therefore, a computational approach requiring the identification of edge points prior to point grouping was found to be inappropriate.

The contaminating effects of edge points on surface features computed at neighbouring points could not be reduced or removed. Instead, edge points were left in the data set in the knowledge that these and other points effected by their contaminating effects would fall out of the clustering process as isolated points. Edge points would not be grouped with 'regular' surface points as they do not exhibit features consistent with the majority of points in the data set, ie significantly larger curvatures.

3.3 Approximating Surfaces.

The initial algorithm development was undertaken using an approximating surface of the type used by Flynn and Jain (1988):

$$w(u,v) = C_1 u^3 + C_2 u^2 v + C_3 u v^2 + C_4 v^3 + C_5 u^2 + C_6 uv + C_7 v^2 + C_8 u + C_9 v + C_{10}$$

This approximating surface was replaced by the one presented in Section 2, as the higher order function behaved poorly in the vicinity of edge points. When used in a least squares fitting process the high degree of freedom of the approximating surface meant that it would often produce a good fit on all data points in the surface patch, regardless of edges. This was at the expense of a suitable representation of the underlying surface. The simpler equation of section 2 produced a surface that fitted a majority of points in the patch without unnecessary oscillations in the approximating surface.

3.4 Surface Normal Directions.

The surface normal directions and their functions are valuable quantities for the decomposition of data sets in both computer vision and target field generalisation.

The continuous data sets used in computer vision applications are less susceptible to ambiguities associated with surface normal computations than the target field data sets. In computer vision applications only a portion of the object is considered (viewed) from a single point. This significantly reduces the range of surface normal directions returned for points on the object. There are no ambiguities caused by normals being returned that are parallel or near parallel but in opposite directions. In computer vision (range data) all surface normals are 'out" of the object, 'towards' the sensor. In addition, occlusions in the images mask out portions of the object in which ambiguous surface normal directions could be computed eg. potentially ambiguous normals perpendicular to imaging direction are not computed. (Figure 4a.)

The data sets representing objects to be generalised in this evaluation have no established perspective and embody the entire object. The surface normals are computed from continuous local approximations of the discrete data set and the surface normal can be on either side of this surface. The surface normals can be 'into' or 'out of' the object. When considering these surface normals there is no limit on the range of directions to be considered. Therefore, parallel and near parallel normals in opposite directions, which are 'similar' despite apparent differences must be accounted for in the clustering process (Figure 4b.)

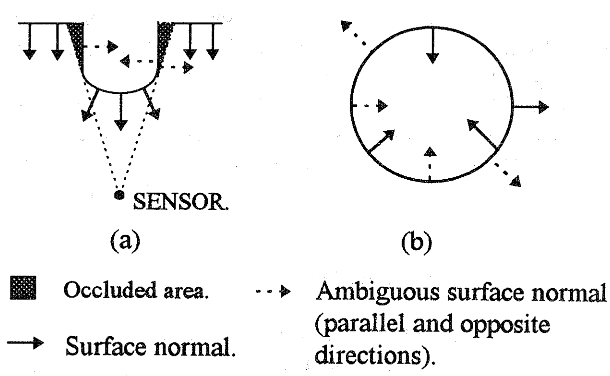

Figure 4. Ambiguous surface normals.

Instead of adding information to the point grouping process the surface normal directions when computed for the entire object tended to only confuse the clustering algorithm. Despite their value the surface normal directions are not suitable for direct input into a clustering algorithm for this application. Instead the value of the surface normal direction needs to be exploited on selected portions of the data set where there range of directions is limited and can be used to resolve ambiguities arising from planar regions in the data set.

4. REFINED COMPUTATIONAL APPROACH.

The minimum and maximum curvatures at a point have been found to be the only uniformity measures that are suitable for direct input into the selected clustering algorithm for this application. These values do not introduce ambiguities or uncertainties into the point grouping process, however considering these two measures in isolation will group points according to surface type alone, ie. planar, cylindrical, spherical and conical. Further processing is required if points on the same surface type but with different orientations are to be split, along with points on the same surface type with similar orientations but in different locations.

Thus, the following processing strategy will be adopted:

- Minimum and Maximum curvatures will be considered in isolation: grouping points according to surface type alone. A two dimensional version of Jolion's algorithm will be employed.
- Points on planes of different orientation will be split by considering surface normal directions for planar portions of the data set in isolation. This, limits the range of normals to be considered, and reduces the complexity of the ambiguities associated with this measure.
- The proximity of points will be evaluated to split points lying on surfaces of the same type, but in distinctly different locations.
- Edge points (ungrouped in a two dimensional clustering algorithm) will be assigned to multiple point groups based on the geometric fit of the point to the underlying surface of each point group.

5. CONCLUSION.

The difficulties encountered in algorithm development detailed in this paper are related to the application of the uniformity and proximity measures to the generalisation of target fields. The problems encountered do not indicate a failing of the uniformity and proximity measures in concept, only in application. The problems associated with the application of these measures will be addressed with the development of the refined computational approach, in which surface curvature and surface normal data are not considered simultaneously.

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