RECONSTRUCTING 3D TRIANGULATED SURFACES USING NORMAL CONSISTENCY AND LOCAL EXTREMES FOR LARGE GEOSPATIAL SURFACES

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ABSTRACT

Geospatial applications that do not demand fine surface details for large geospatial features can use polyhedral description of the surface. Triangulation from set of points dispersed in 3D space is a method of preference to generate such polyhedral surfaces suited for computer vision based applications. Surface triangulation based methods are used to overcome the problems related to rendering large geospatial objects and memory constraints related to it. This paper presents a framework for generating a 3D triangulated surface of large geospatial terrain like data by computing surface extremes together with normal consistency and compares it to that of reconstructing triangulated surface using other known methods performed on LiDAR data. The proposed method demonstrates the effect of local and global surface extremes on surface triangulation and assessing the quality of the surface from pruned points in 3D space. It also demonstrates the usefulness of density controlled curvature discontinuities in defining the structure of the surface. Problems related to holes or missing data has been successfully addressed. Our method combines oriented and non-oriented points for globally consistent triangulation. Results are compared to other methods and found better in rendering 3D profiles and demonstrates visually consistent and improved surface.

Keywords: 3D Reconstruction, Surface Visualization, Surface profiling, Triangulation

[1] INTRODUCTION

Data visualization and object reconstruction have emerged as a key enabler for understanding geographic objects, features, and phenomenon around us. Importance of reconstruction of objects in geographical information systems (GIS) based application is more evident with the advancement in computer vision and related field. Most of the object reconstruction methods have largely focussed on small structures and focussed on using mathematically defined surface definitions for applications including restoration and rebuilding of objects. However, large geospatial structure especially those which are defined using unstructured points needs a different approach for simple reasons of efficient rendering and reduced complexity. The problem of reconstruction and visualization of geospatial objects in 3D space using unstructured points needs attention as it suffers from high computational and storage requirements. The problem of reconstruction is more complex for non-uniform irregular surfaces such as terrain, sand dunes, and mountain cliffs. Among all methods[1], surface triangulation
offers a better prospect of representing surfaces and flexibility especially from a set of points dispersed in 3D space such as point clouds. However, there are further opportunities to generate triangulated surfaces by considering and pruning surface points.

Some application requires only structural approximation and do not require minute details of the surface compositions. A less detailed yet sufficient structural information can lead to optimization in storage as well as rendering large geospatial objects. The facet or polygonal approach as discussed in [2], [3] helps in this situation but lack from capabilities for highlighting sharp curvatures and surface continuities. Theoretical studies suggest that detecting and developing surface profile using optimized skeletal mesh can provide a more optimized alternative for representing and rendering the surface. These representations offer reduced space complexity and improved rendering performances at runtime. Generating a shaded model from these models is more relevant and useful especially when fine details are not desired. Computer vision and geospatial analysis for large landscapes can benefit from this approach.

Skeletonizing and extracting related structural profiles of any object can offer a minimalistic way of representing large and complex objects. While 2D skeleton based representation is sufficient to highlight the structural and shape-based information about any object, a 3D or near 3D representation of objects may further need secondary processing to define the surface characteristics of interest. Rather than using the internal 3D skeleton, surface discontinuities and curvature continuities can be more useful. Large geospatial objects which including landforms and terrain profiles can use this approach for representation as well as 3D reconstruction in an optimally controlled setup. The task of determining surface profiles is challenging especially when the surface is defined using spatial distribution of points in 3D space.

Surface discontinuities and curvatures in geographical surfaces are a result of natural phenomenon. These exhibit small and big abrupt changes in height and elevation values. We can extract this information from the given surface details and reconstruct objects with minimal point attributes. There is further scope for exploring possibilities of reconstructing 3D geospatial objects in from these surface extremes. In this paper, we describe an optimal way to describe and reconstruct objects of geographical nature that exhibit fasts curvature discontinuities and rapidly varying surface characteristics. The problem of surface reconstruction considers a point cloud comprising of set of unorganized point set $P = \{p_i\}$ defined in R3 for $i = 1,2,3,...,n$, and approximates surface as collection of triangulated $P(T)$ faces. The triangulated faces are set of three points from $P$ that satisfy triangle property. The proposed method relies on estimating sharp curvature and pruning surface discontinuities. The algorithm combines triangulation obtained from oriented and non-oriented points. The proposed method uses pure 3D approach and detects surface profiles to define a structural feature of the pruned geospatial object. Pruning of surface discontinuity eliminates non-essential surface details and helps to reconstruct and visualize objects using surface skeletons.

[2] RELATED WORK

Reconstruction of 3D objects has been addressed in many dimensions. Some of the recent developments have been described in [1] and [4]. The usefulness of these reconstruction finds several applications as in [5], motivates generating optimized triangulated surfaces with reduced geometrical complexity. As a problem of reverse engineering from the scanned unorganized point, methods like 2D-manifold triangulation discussed in [6] gives a pathway towards generating lightweight surface details especially when fine details are not required. It describes creating and merging local triangular developments but considers all points given in the space. The strength of the algorithm resides in the fact that it was based on computing neighborhood graph and handle holes and open boundaries. However, all computations relied on 2D computations.

A little different but effective approach that combines the simplicity of the 2D approach and approximation in 3D space is demonstrated in [7] and [8]. Both these methods used projection-based approach. One of the contributions salient feature of the method used in [7] was the use of point pruning using an axis-aligned box of suitable dimensions cantered at the reference point. The points within the box contributed to the surface details. One way to overcome the global nature of point behaviour is
described in this paper. Panoramic 3D reconstruction in [8] used two catadioptric cameras. It combined points obtained from combining refraction and reflection, but exhibited erroneous reconstructions in perpendicular planes.

Optimized triangulated surface generation[9] explains Mesh3D algorithm and explains how sharp edges can be used to achieve efficient and visually correct surfaces from unstructured point samples. This method considers a threshold distance, detects edges fits plane into different groups and generate the triangulated surface. The efficiency of the algorithm was tested on smaller objects and its performance on the large geospatial objects is not tested. Another attempt to generate triangulated surface described in [10] explains the use of Moving Least-Squares (MLS) in representing surfaces. This method was independent of normal. The methods were tested on smaller objects and their performance over large geospatial surface has a performance issue. Use of spherical topology in surface approximation [11] based on [12] presents an optimized surface texture defined in 3D space. It highlighted that the surface geometry of the original data points controls and defines a data-dependent triangulation.

Some other relevant works relating to 3D reconstruction from point samples are seen in [13],[14] and [15]. The smooth surfaces of order $C^2$ and homeomorphic to the original surface has been used in [15]. In all studies related to 3D reconstruction from point samples, major work has been concentrating either on Delaunay triangulation or direct method including those designed around Ball pivoting method[3]. There is further scope to improvise 3D reconstruction of surfaces from point samples in 3D space. The details of the proposed method are discussed in detail next.

[3] THE 3D GEOSPATIAL RECONSTRUCTION PROBLEM

Reconstructing surfaces from an unstructured set of points in 3D space is challenging due to the fact points as a primitive structure contains limited information that too about the small local section of the surface. It is difficult to decide about how the surface behaves between the set of any adjacent points. The problem of 3D reconstruction further aggravates if the point sample is sparse or distributed unevenly. Sharp spikes and extreme point samples further add to the complexity of surface generation possibilities. For a large class of applications, these surface extremes only add to redundant information and often can be suppressed. Sampling solves the problem to a limited extent as the presence of noise and local extremes make surfaces more complex. Some of these points that are likely not to add to the surface triangulation $P(T)$ can be culled away satisfying the condition $P(T) \subseteq P$. These set of points are chosen from set of neighbors $N(p)$ for any point $p \in P$.

It is to be noted that outliers in the data set are often due to acquisition errors, noise caused by the location errors in storing them in 3D. However, it is hard to determine the distinction between outliers, inaccurate measurements, and surface extremes. Such points can be extracted and smoothened and integrated for surface generation. One way to deal with these problems is pruning the probable surface points and generate smooth surface profiles and construct the surface. For reasons of efficiency in rendering and visualization, triangulation of these pruned surface points is considered and evaluated. Among several parameters that affect the quality of surface triangulation includes a search radius($r$), number of neighbors($N(p)$), minimum and maximum angles ($\theta$) and consistency of normal $\hat{n}$ along vertices at the edges. The results in better visual experience aspects and number of cells on the generated surface.

The outline of the proposed framework for the surface 3D triangulation is given below.

[4] FRAMEWORK FOR SURFACE TRIANGULATION NORMAL CONSISTENCY AND LOCAL EXTREMES

Large geospatial surface suffer from approximation anomalies while using Delaunay triangulation methods and sometimes results in less satisfactory surfaces. An improvement is seen using greedy projection based triangulation as discussed in [16] and [17]. The proposed framework evaluates the significance of algorithm based on surface extremes and normal consistency for triangulating...
surfaces including large geospatial landscapes. The outline of the proposed framework is presented below.

1. Eliminate outliers \( O \)
   \[ O = \{ p | p \in P ; \int_{r=\alpha}^{\beta} \mu_r(p) = \phi \} \]
   Where, \( k \) denotes \( k \)-nearest neighbor and \( \rho \) denotes sample density/resolution.

2. Spatial Interpolation and gap filling
   a. Compute Gap \( G_k \)-the sub space with no points
   \[ G_k = \{ S | S \subseteq P , \int_{x,y,z} count(S) = 0 \} \]
   b. Apply trilinear interpolation along dimensions of the 3D grid, where interpolation problem is formulated as
   \[ f(x,y,z) = a_0 + a_1 x + a_2 y + a_3 x + a_4 xy + a_5 yz + a_6 xz + a_7 xyz \]
   Where \( a_i \) denotes coefficients and \( x,y,z \) are directions along spatial axis.

3. Compute surface extremes and surface knots
   a. Computing surface extremes \( p_{k_e} \)
   \[ p_{k_e} = \int p_{xyz} | dist(p_{xyz}, P) \geq k \]
   \( p_{xyz} \) is the adjacent point connected to current point \( P_i \).
   b. Compute surface knots using pruning function
   \[ p_{k_e} = \max_{z}(p_{k_e}, z) \]
   Where, \( \max_{z}(p_{k_e}, z) \) computes point with maximum \( z \) in local neighbors.

4. Compute Triangulations
   a. Triangulate without normals controlled by \( \theta_{\text{min}} \) and \( \theta_{\text{max}} \)
   b. Triangulate with point normals such that face orientation change satisfies \( \Delta \theta \geq \theta_{\text{threshold}} \)
   where, \( \Delta \theta = \tau_i - \tau_j \) for adjacent triangles \( i \) and \( j \) respectively. \( \theta_{\text{threshold}} \) is determined empirically.

5. Combine surfaces obtained from steps 4a and 4b to obtain final surface.

6. Post processing and exports for geo-visualization

Note that, step 1, eliminates outlier points from the data samples. These points are points who have no neighbors beyond an empirically determined distance in 3D space within the spherical envelope. Such points are culled away. These points are usually the result of errors during data acquisition. In order to normalize the surface and maintain continuity of surface, step 2 fills holes (if any) through interpolation. Step 3 extracts surfaces extremes in \( \mathbb{R}^3 \) space for the entire surface. The objective of this stage is to extract the control profile of the surface defining the surface morphological structure. The pruning function is a sharpening filter that identifies a set of extremes among collocated setoff points. In step 4, the initial seed triangle is taken randomly from one of the extremes and triangulation is performed satisfying the Delaunay conditions each of the cases corresponding to step 4a and 4b respectively. More insight into the proposed methods of surface triangulation is presented in the following discussions.

[5] MORE ABOUT PROPOSED SURFACE TRIANGULATION METHOD

Contrary to structuring of surface points using axis-aligned box[7], this paper proposes the use of collocated points within spherical envelop and prunes them for determining control profiles for surface triangulation. The method also uses pruning function for identifying contributing points that define the shape of the surface in \( \mathbb{R}^3 \) space. It solves two purposes. Firstly, it extracts sharp extremes and outlier points within a controlled neighbourhood \( N(v) \). Second, these sharp extremes are used to define surface knots \( k_i \) that help to bind the triangles on the surface. These sharp extremes are defined as knots that control profiles on the surface exterior and adapts to different densities of points in the space.
The point cloud is analyzed for regions of sparse distributions and missing data (if any) and follows the procedure to spatially interpolate them for filling of gaps for generating smoother surface profiles. Traditional linear interpolation is extended in three-dimension, something similar to trilinear interpolations. This generates and updates the distribution of point sample and offers better spatial continuity. Holes having a diameter larger than $2\rho + 1$ will see less or no interpolation due to dilation at the boundaries. During the reconstruction process, when sampling has no candidate points, these interpolated points add to the neighbors and contribute towards further triangulation.

The proposed method uses point samples in two perspectives for the purpose of surface reconstruction. One that considers normal consistency while choosing next neighbour point and other are those without constant normal. The advantage of this approach is that it can offer better capability to handle more complex point sets as it generates surface from two samples rather than one homomorphic surface. The points with normal define the key shape features from real world coordinates. Contrary to it, points when considered without normal gives freedom for approximation of surface structure especially in regions of missing point samples. The points that would possibly contribute to the surface are determined and controlled by search radius which effectively can be a geodesic distance. Euclidean distance is used for computing this distance from the point $p$ to any point $q$ such that $p, q \in P$. The set of neighbors of point $p$ within a radius $r$ is represented by $N_r(p)$ is determined as follows

$$
N_r(p) = \{ u \in P ; \| p - u \| < r \}
$$

The choice of $r$ is influenced by the resolution of the sample point data under investigation. The resolution here is also influenced by the density ($\rho$) of the given point cloud. The sampling resolution of the data used in experimental verification is 30m organized as airborne point cloud. For optimal surface triangulation and, to reduce unnecessary computational overheads, the value of $r$ is theoretically suggested to be twice or more of the density of the data. This hypothesis is also empirically found to satisfy the relation $0 > r \geq 2\rho$ and $N_r(p) \neq \emptyset$. The value of $r > 2\rho$ would result in the surface of near similar quality as the number of triangular cells formed remains invariant. Some regions covered by the data may have a high local distribution of points, have sparse distribution, or may have no data points at all. In such cases, the points contributing to the triangulation would be determined by the $k$–neighborhood of point $p$ denoted $N_k(p)$. The value of $k \geq r$ can be interactively obtained for the required quality of the surface.

The surface reconstruction process combines triangulated surfaces generated point with and without point normal and generates fusion surface. The benefit is clearly visible in output (see Figure 6d). The resulting triangulated surface has more controlled triangulation through surface extremes and highlights local variations and exhibits directional attributes that are suited for rendering and shaded appearances.

[6] DATA DESCRIPTION

The experimental data mandates the use of point cloud obtained from light based sensors like LiDAR. The point cloud LiDAR data used for experimental verification of the proposed framework is
adapted from dataset used in [16] for a limited area representing Coastal Dune Fields. The data has a resolution of 30m and recorded as ASCII coordinates using WGS84 coordinate mapping. The experimental data has non-uniform densities of point distribution across the sample landscape with an average of 2.13 points/m². The input cloud is translated from ASCII o PCD format for processing purpose. Distinctively the z coordinates associated with each spatial point in space is analyzed and processed during triangulation. For visual verification, the results obtained after the experiment are visualized using libraries like PCL and open source and propriety tool like CloudCompare and Paraview®. The results of the experimentation on the data using the proposed framework are discussed next.

[7] EXPERIMENTAL RESULTS AND EVALUATION

The observation from the reconstruction using the proposed method gives good results for the given point cloud data and stand by most known surface reconstruction methods. The input to the algorithm is the point cloud of 30m resolution in raw ASCII format without any color components. Less than 0.05% points were classified as an outlier and culled away resulting into 92970 points. Nearly 6% of the coverage was classified as holes and gap filling using trilinear interpolation reduced it to 4.5% making the point sample with 97863 points. Next, the surface extremes are computed and it amounts to around 12% of the total point samples. Key surface knots are also computed.

Table 1 demonstrates the performance of the triangulation with and without normal continuity and further improvements in surface coverage by fusing them. The proposed framework generates a triangulated surface with 254205 cells for search radius 𝑟 = 100, 𝑘 = 200, its maximum surface angle set at 45°, and minimum and maximum angle for triangulation set at 10° and 120° respectively. Table 2 gives sample output for different values of surface and angle for triangulation.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Triangulated Surface Cells</th>
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<tr>
<td>No Normal Continuity (A)</td>
<td>Normal Continuity (B)</td>
</tr>
<tr>
<td>25397</td>
<td>254127</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Triangulated Reconstruction Performance (𝑟=100, 𝑘=200)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Cells</td>
<td>No. of Points</td>
</tr>
<tr>
<td>252159</td>
<td>97863</td>
</tr>
<tr>
<td>253660</td>
<td>97863</td>
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<td>263554</td>
<td>97863</td>
</tr>
</tbody>
</table>

The performance of the proposed framework for the surface triangulation showing the effect surface angle, minimum and maximum angles for triangulation with and without normal are shown in figure 1. Figures 2 shows analysis of standard variation and error estimates for results obtained for various methods. These are evaluated on parameters such as the number of cells, computational time and geometry size. Figure 3 and Figure 4 demonstrate the performance based on computational time and the number of cells produced on the resulting surface using various methods. The triangulated surface from points associated without normal and also with normal is computed for the same set of parameters.
The final surface is obtained by fusing both triangulation. Triangulated Mesh model and flat shaded surface showing contribution with and without normal is shown in figure 5a and 5b respectively. The surface angle is fixed at 45° and minimum and maximum are set at 10° and 120° respectively.

a. Mesh Model showing Superimposing Triangulations with and without Normal Continuity
b. Flat Shaded Triangulated Surface Highlighting Contribution of Normal Continuity

**Figure 5.** Transforming triangulated Mesh to shaded surface showing contributions from surface with normal continuity, without continuity and fused regions.
Some of the salient observations and findings based on experimentation are listed below.

i. The memory requirement and geometry size of the resulting triangulated surface remains largely invariant compared to that of the surface angle across the surface.

ii. Improved surface approximation and spatial coverage are obtained for angular limits between $0 < \theta \leq 2\pi/3$.

iii. Use of surface knots together with extremes define and control the surface profile and show crisp local highs.

iv. Merging two surface triangulations viz. one obtained from points with normal and second without normal continuity produces better surface coverage.

v. Surface like terrain and sand dunes can be approximated by considering normal consistency and local extremes for better results.

While the proposed method requires has higher computing time to that of greedy projection and simple Delaunay triangulation, this shortfall is overcome by the improved surface triangulation and better coverage of the landscape. Simple triangulation has considerably less number of cells at the cost of higher computing time due to the fact that more comparisons are made before triangulation is made. Use of normal continuity help is generating smoother transition among adjacent triangle cells and thus result in improved visual performance. The results on the sample data demonstrate that for large landscapes, unstructured data organized as point cloud is useful and helps in extracting and visualizing surface deformations with better rendering performance. The intermediate results for surface are shown in Figure 6.
[9] CONCLUSION

It is experimentally demonstrated that out of all points in the sample data, surface extremes control the shape of the surface and contribute most in determining surface profiles. Quality of the surface obtained by fusing surface generated from points with and without normal is better than those generated individually. The theoretical hypothesis of the number of cells required for generating surface from the given set of the point is also validated and found to be twice or more to that of the number of point samples. The Quality of the surface is relatively better than projection based methods of triangulation and also to those based on direct triangulation methods. The computational time in the proposed methods is compensated by the quality of surface triangulation and compares better to that of simple triangulation. It also set pointers for the future research for optimizing surface quality by formulating blending surface s obtained from pruned set of surface extremes and normal continuity.

REFERENCES