Feature curve extraction from data points

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Abstract: In the present work, study is done for the extraction of feature curves from data points lying on the surface of object or model. Here, the reconstruction of feature curves is proposed by intersection of plane pairs. These plane pairs approximate the adjacent regions of the feature. Feature of the object may be its edges, corners, holes, sudden jerks, slits etc. Points cloud is generated from the snapshots of the object taken from various viewing angles. Clustering work is extended from K-means clustering to combined K-means and Normal (attribute) approach based clustering as it utilizes the benefits of both K-means and attribute based method and segmented the data points so that a cluster is represented with similar normal vector. Planes are fitted to all clusters based on Least Square Plane Fitting (LSPF) method and line segments from their intersection are identified, highlighted and collected as feature lines i.e. edges and corners based on developed algorithm.

Key words: Points cloud, Sharp features, Feature curve, Developable surface, Clustering

1. Introduction

Feature of any object or models means something on that body which gives us its geometrical information like its shape, size, curvature etc. Also feature curves lie on the boundary, edges and other sharp geometry. In this paper, a study is done for finding out the feature curves from data points which has various applications in model reconstruction, shape matching, geometry compression etc. The data points are obtained from object's surface in the form of point cloud by various methods like coordinate measurement machine, optical 3d scanners, image processing techniques etc.

As feature curve extraction has numerous applications so it has attracted attention of researchers. Chica[1] used dense point cloud for extracting feature curves. The point cloud was converted to discrete volume representation which was further used for the computation of visibility map for finding out the vertices, edges and faces. A semi automatic approach for free form surfaces is presented by E. Dekkers et. al.[2] for finding the feature curves. The process take place by initial curve generation, curve dragging and feature curve optimization. Dey and Wang[3] used Voronoi based method for finding the feature curves.

Lee & Pengbo [4] initially approximated the data points by developable surfaces. Further intersection of these developable surfaces is used to obtain the feature curves. Feature extraction using multi step method was proposed by Daniel et al. [5]. Feature points were initially identified by using RMLS (Robust Moving Least Squares) operator. These points were further projected on the intersecting planes near to the feature.
Weber et al. [6] analyzed the neighborhood of points using PCA (principal component analysis). The eigenvalues of the correlation matrix were used to find the probability of a point belonging to a feature. Also feature type (like line, corner point etc.) were analyzed using eigenvalues and eigenvectors. Pauly et al. [7] used multi scaling approach to obtain the information. Gumhold and Wangy [8] also worked for feature lines extraction from data points. Some research work has been done for developable surface fitting on point cloud [9-12] which are further used for extraction of feature curves. After getting the feature curves they are sequenced and joined to get approximate feature curve or edges. Daniel et al [5] proposed a method that initially finds the sharp features. Further smooth curves are obtained which are aligned along the edges. This multi-step method initially fits the local surfaces by least square which are further used to find the potential features. Yi et al. [13] proposed a method which extracts features using discrete curves.

2. Overview of algorithm
In the present work point cloud of an object is generated through photographs of the object taken from various viewing angles. Further 3DF Zephyr software was used for obtaining the point cloud from these photographs. The obtained point cloud is used for further processes.

The present work is divided into mainly four parts namely: 1.) Normal vector estimation 2.) Cluster formation 3.) Surface fitting 4.) Feature curve extraction

3. Normal vector estimation
The normal vector data is used as an attribute along with K-Means algorithm [14] for clustering to get desired clusters. Normal vectors are estimated through PCA (Principal Component Analysis) [15] method and by using point cloud library (PCL). In PCA normal vector is taken as principal component which is estimated through neighborhood approach. Further in this approach each point is considered as a vector of three random variables (x, y, z). Some insights on local variations of points can be found by using the covariance matrices. Neighborhood of a point can be found using K Nearest Neighbor (KNN) Method. These covariance matrices show the dispersion of neighborhood around the centroid.

The smallest Eigenvectors of the covariance matrices indicate the normal vectors of planes best fitting to these neighborhood points because each eigenvector shows a direction of principal variations. Out of these eigenvectors, the eigenvector having the smallest eigen value shows the direction of least variation which is geometrically perpendicular to the direction of most variations. Hence the eigenvector with smallest eigenvalue gives the normal vector of the plane which is best fitted to the neighborhood points.

The mathematical expression shown by eq.(1) below represents a 3 by 3 symmetric covariance matrix which is used to find the normal vector of the point Pt. Here A[Pt] is the average of all neighboring points given as eq.(2). An Eigen system is formed for this covariance matrix using a linear algebra library, and the eigenvector corresponding to the least eigenvalue is taken as the normal vector at each neighborhood points.

\[
\text{Cov}(P_t, P_t) = [(P_t - A[P_t]).(P_t - A[P_t])^T] \quad (1)
\]

\[
A[P_t] = \frac{1}{k} \sum_{i=1}^{k} P_t \quad (2)
\]

4. Cluster formation
Clusters are formed on the basis of K-Means algorithm along with using normal attribute. It is an iterative process and the data points belonging to a cluster are initially determined by distance between them. This approach is called Expectation-maximization i.e. E Step-M Step. The data points are assigned to the closest cluster by E step. Further M step is used to find the centroid of the cluster. It is started by selecting the seed points randomly. These seed points are considered as centroid initially. Further clusters are grown by joining neighborhood points. This is done by joining a data point to the closest cluster having similar normal vector and the minimum of Euclidian distance between data points and all centroid points. Further
centroïd of the cluster is updated by taking the average of the data points belonging to that cluster. The process is repeated till all the data points join to some cluster and there is no independent point left.

5. Plane fitting

In the present work surface fitting to each cluster is done by using least square plane fitting (LSPF) since each cluster of points is approximately planar. Plane is the locus of lines that have direction vectors perpendicular to a normal vector. It works on the principle of minimizing the summation of squares of error in distance of each point from the plane. In case of clusters belonging to non-planar surfaces Least Square Surface Fitting (LSSF) is required to be done in place of LSPF. Let $P_t$ is a set of $n$ data points in a cluster given as

$$P_t = \{pt_1, pt_2, pt_3,\ldots, pt_k,\ldots, pt_n\}$$

The data points in the set $P_t$ are represented by their Cartesian coordinates like point $pt_k$ is represented by its coordinates $(x_k, y_k, z_k)$. Further let plane $ax+by+cz+d=0$ is considered to be fitted on the $n$ data points of the cluster. However it may be possible that the data points do not fall on the fitted plane. Let $e_k$ represents the distance between a point and fitted plane as given in eq.(3)

$$e_k = \frac{|(ax_k+by_k+cz_k+d)|}{|n|}$$  \hspace{1cm} (3)

Here $n$ is the normal vector of the plane.

Best fitted plane is achieved by using least square method by minimizing $E$ in eq.(4) given below.

Let

$$E = \sum_{k=1}^{n} e_k^2$$ \hspace{1cm} (4)

6. Feature line extraction

In the present work edges are the linear feature curves and corners are the feature points. Linear feature curves or edges are found out by intersection of two adjacent surfaces and corner points are obtained by intersection of three adjacent surfaces. Further only those edges are selected which are having dihedral angle more than the specified threshold value. Dihedral angle ($\theta$) is computed by using eq.(5) as follows.

$$\theta = \cos^{-1} \left( \frac{n_1 \cdot n_2}{|n_1||n_2|} \right)$$  \hspace{1cm} (5)

Here $n_1$ and $n_2$ are the normal vectors of the two adjacent planes.

Further if eq.(6) and eq.(7) represents the two adjacent planes then the common points lying on the two represents the edge at which they are intersecting to each other which can be found by solving eq.(6) and eq.(7).

$$P_1 = A_1X + B_1Y + C_1Z + D_1$$ \hspace{1cm} (6)

$$P_2 = A_2X + B_2Y + C_2Z + D_2$$ \hspace{1cm} (7)

Further the obtained edges are joined at their common boundaries to get the final feature curve.

7. Results and discussion

Bed Table is taken as an object for applying the algorithm discussed in the previous sections as shown in fig. 1.

![Figure 1. Bed table](image-url)
45 photographs of it were taken from various viewing angles. Out of these 45 photographs some of the photographs showing more viewing variations are shown in fig. 2.

Figure 2. Photographs of bed table from various viewing angles

Further 3D point cloud of bed table was obtained by 3DF Zephyr software by using these 45 photographs after doing masking and cleaning process manually. Fig.3 shows the outline drawn for masking operation. Masking removes the data points belonging to far away objects.

Figure 3. Masking

After masking operation some erroneous data points still exist which can be seen in fig.4. These erroneous data points are removed by cleaning process.
Finally after all these processes a neat and clean point cloud of bed table is obtained as shown in fig. 5. Here data points only belonging to the object can be seen and no other data points are visible.

Further normal vector estimation of the data points is done as explained in section 2. Normal vectors obtained on data points are shown in fig. 6. Enlarged view of it is also shown in fig. 7. From fig. 7 it can be seen that the normal vectors are shown in the form of arrows. The direction and length of the arrows represent the direction and magnitude of normal vector respectively.
K-means and normal attribute approach as explained in section 4 was applied to obtain the clusters of data points. For the same initially 41 seed points were selected randomly representing the centroids of the respective cluster. Further data points were joined to these clusters as explained in section 4. Fig. 8 shows the obtained clusters.

![Figure 8. Clusters of data points](image)

Clusters having similar normal vectors and common boundaries were further merged. These clusters were fitted with surfaces which are planes in the present case as explained in section 5. The fitted planes are shown in fig. 9.

![Figure 9. Planes fitted on the clustered data points](image)

It can be seen from fig. 9 that clusters fitted to the same plane are represented by same colors so that the various planes on the object can be seen visually and hence, distinguished from each other. Intersection of adjacent planes is computed as explained in section 6 to obtain the edges or feature curves. Further intersection of the edges or three adjacent planes is used to obtain the feature points which in the present case are corner points. Obtained edges and corner points for bed table are shown in fig. 10. Edges are shown by brown colored lines and corner points are shown by yellow dots (Fig.10). Feature curves (edges) and feature points (corner points) are also shown on the point cloud data in fig.11.

![Figure 10. Edges and corner points on bed table](image)  ![Figure 11. Edges and corner points in point cloud data](image)
Finally it can be seen from fig. 10 and fig. 11 that the feature curves and feature points obtained from the proposed algorithm lies at the position where they physically appear to be on the object (bed table).

8. Conclusion

In the present work a method is proposed for the extraction of feature curves and feature points from points cloud obtained from an object. The proposed approach was applied on bed table as an object to test the algorithm. Here, clustering work is extended from K-means clustering to combined K-means and Normal (attribute) approach based clustering which gives more satisfactory results. Further planes are fitted to all clusters based on LSPF method and line segments from their intersection are identified, highlighted and collected as feature lines. Also the intersecting point of 3 neighborhood planes are identified and collected as feature points.

Future scope of this work is to find the appropriate number of clusters and smoothness of the final reconstructed curves.

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