Selection of Regions on a 3D Surface for Efficient LIDAR-based Pose Estimation

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Abstract

This paper presents an innovative approach for the selection of well-constrained surface regions for efficient pose estimation using LIDAR range scanning. The selection is performed using Continuum Shape Constrained Analysis (CSCA). This technique uses indices, numerical combinations of eigenvalues of the error matrix, which are used to predict pose estimation accuracy for different scans of the same object or different regions on the surface of a particular object's scan. Localized scanning is essential when only certain regions of the surface are available for scanning. To illustrate the proposed CSCA approach,this paper uses a newly developed Expectivity Index. The area selection process was successfully demonstrated on (a) a faceted shape with supporting experimental results obtained with Neptec TriDAR scanner, and (b) a model of the Stanford Bunny as an example of a general shape.

1 Formulation of Continuum Shape Constraint Analysis for ICP Registration

A range-finding scanner samples an object's surface to produce a cloud of data points which is then used in the Iterative Closest Point Algorithm (ICP) [1] to compute the pose of the object. A continuous surface model of the object is, generally, given as a triangulated mesh. This paper mainly focuses on the terminal accuracy of the ICP algorithm in the context of imperfect input data and the sensitivity of the pose solution in the vicinity of the true pose to the inevitable presence of noise-like error. Geometric constraint analysis (CA) examines the sensitivity of shape registration error to variation in the model's pose, providing a powerful way of assessing the expected accuracy of iterative registration algorithm. CA has an attractive feature of being bases on bulk calculation of data, avoiding feature and invariants detection tasks. Simon in [2] introduced the application of constraint analysis to pose estimation and used the Noise Amplification Index (NAI) to assess the quality of registration of human bones for radiation therapy. Later, Shahid & Okouneva [3] used the same form of discrete point constraint analysis applied to point clouds collected from the uniform projection of points onto "window" areas of spacecraft objects in order to identify a view for optimal scanning. A more recent paper by McTavish & Okouneva [4] generalized the concept of discrete-point self-registration to a surface-integral based self-registration referring to it as Continuum Shape Constraint Analysis (CSCA). It is based on the concept of self-registration, wherein a registration cost is generated for a differential movement of the shape relative to itself.

The continuous self-registration cost function minimized by ICP algorithm is $E = \frac{1}{2}p^T\mathbf{E}p$ where $p = [\delta, D\theta]^T$ is a small pose vector and D is a scale factor which balances the contribution of translation and rotation. The cost function is dependent on the view factor $v(\mathbf{r}, \hat{\mathbf{v}})$ and can be represented as

$$\mathbf{E} = \frac{1}{A_p}\int_S \left[\begin{array}{cc} \hat{\mathbf{n}}\hat{\mathbf{n}}^T & -\frac{1}{D}\mathbf{r}^\times\hat{\mathbf{n}}\hat{\mathbf{n}}^T \\ \frac{1}{D}\mathbf{r}^\times\hat{\mathbf{n}}\hat{\mathbf{n}}^T & -\frac{1}{D^2}\mathbf{r}^\times\hat{\mathbf{n}}\hat{\mathbf{n}}^T\mathbf{r}^\times \end{array}\right] v dS$$

$$v = v(\mathbf{r}, \hat{\mathbf{v}}) = \left\{\begin{array}{cc} \hat{\mathbf{v}}^T\hat{\mathbf{n}} & \text{when } dS \text{ is unobstructed,} \\ 0 & \text{when } dS \text{ is obstructed} \end{array}\right.$$

$\hat{\mathbf{v}}$ is a view direction vector, $\hat{\mathbf{n}}_i$ is a unit normal, A_p is the projected onto $\hat{\mathbf{v}}$ area, and the vector-matrix cross construct operator is

$$a^\times = \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix}^\times = \begin{bmatrix} 0 & -a_z & a_y \\ a_z & 0 & -a_x \\ a_y & a_x & 0 \end{bmatrix}.$$

The Expectivity Index (EI) is defined as $K_{EI} = \left(\sqrt{\sum_k \frac{1}{\lambda_k}}\right)^{-1}$ where $\{\lambda_k\}$ are the eigenvalues of the matrix $\mathbf{E}$. For zero-mean random noise error with the standard deviation σ_ε, EI is related to the standard deviation of the estimate of the pose-error magnitude as follows: $\sigma_{\mathbf{p}_\varepsilon} = \frac{\sigma_\varepsilon}{\sqrt{\rho_p}} \cdot \frac{1}{K_{EI}}$, where $\rho_p = \frac{N}{A_p}$, and N is the number of points. This formula indicates that the higher the EI value is, the lower is the value of $\sigma_{\mathbf{p}_\varepsilon}$. Therefore, the "best" and the "worst" windows for scanning are the windows with the highest and lowest EI value respectively. The CSCA approach was demonstrated using a symmetrical cuboctahedron of the radial size $R_C = 127.5$ mm and the Stanford Bunny model of size $R_B = 1.0$ units (Figure 1).

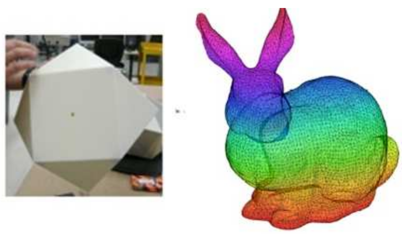

Figure 1: Models of Cuboctahedron and Stanford Bunny

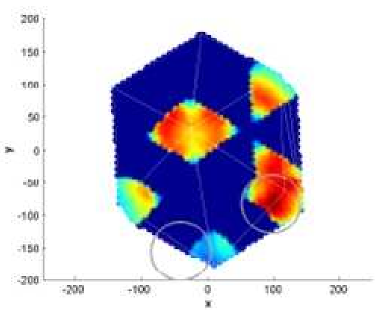

Figure 2: Well and Poorly Constrained Windows for Cuboctahedron, Window Size = $0.25R_C$

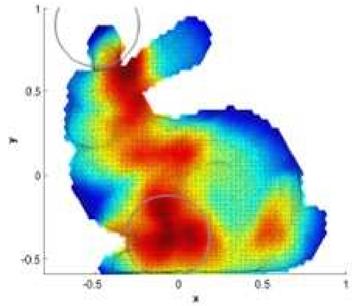

Figure 3: Well and Poorly Constrained Windows for the Stanford Bunny, Window Size = $0.5R_B$

A movable circular window across the entire domain of the view was generated, and the EI was calculated for each window. Figures 2 and 3 demonstrate the EI maps and the "best"and the "worst" windows for one selected medium window size. Each coloured point on the graphs represents the EI value (from "high" red to "low" blue) for the window centered at this point. Localized scanning has a potential to reduce computational cost by allowing the optimization of number of scan points.

2 Acknowledgement

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