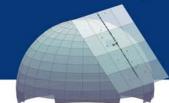


Camera Pose Filtering with Local Regression Geodesics on the Riemannian Manifold of Dual Quaternions

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Smooth Filtering of Rigid Motion Sequences

Tasks such as 6D object tracking and camera pose estimation can produce noisy and inaccurate data series. We present a parameter-free moving window approach to robustly filter these pose sequences exploiting the structure of the dual quaternion space by:

- 1. Identifying the pose series with consecutive points on the Riemannian manifold of unit dual quaternions \mathbb{DH}_1
- 2. Local linearization of the 6D pose space \mathbb{DH}_1 around a support point from the sequence
- 3. Trajectory smoothing by robust linear regression on the tangent space

Quaternion and Dual Quaternion Space

A quaternion $q\in\mathbb{H}$ can be used to describe a rotation in 3D space with the sandwich product [1]

$$\mathbf{p} \mapsto \mathbf{q} \cdot \mathbf{p} \cdot \bar{\mathbf{q}}$$

where the point quaternion ${\bf p}$ depicts the point of interest and the rotation quaternion ${\bf q}$ represents the rotation. A rigid body motion is usually treated as $\mathbb{H}_1 \times \mathbb{R}^3$.

A dual quaternion $\mathbf{Q} = \mathbf{r} + \varepsilon \mathbf{s} \in \mathbb{DH}$ with $\mathbf{r}, \mathbf{s} \in \mathbb{H}$ can be used to describe a rigid motion with the sandwich product [2]

$$P \mapsto Q \cdot P \cdot \hat{Q}$$

where the dual pure quaternion \mathbf{P} depicts the point of interest and the unit dual quaternion \mathbf{Q} represents the displacement. Rotation and translation are treated jointly in \mathbb{DH}_1 .

 \mathbb{H}_1 and \mathbb{DH}_1 are Lie groups. Exponential and logarithm maps can be obtained via parallel transport [3].



Robust Motion Stabilization

A motion can be interpreted as a pose trajectory in \mathbb{DH}_1 . We perform a principal component local regression on the tangent spaces along the pose sequence [Algorithm 1]:

- 1 Set local window around x_i
- ② Map points \mathbf{x}_i^k to tangent space $T_{\mathbf{x}_i} \mathbb{DH}_1$
- ③ Linear regression on $T_{\mathbf{x}_i} \mathbb{DH}_1$ and project \mathbf{x}_i 3.1. PCA 3.2. wPCA 3.3. IRLS [Algorithm 2]
- (4) Map $\mathbf{x}_i^{\text{proj}}$ back to

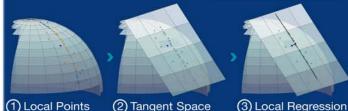
 $\label{eq:Algorithm 1 Manifold Regression.} \begin{tabular}{ll} \textbf{Algorithm 1 Manifold Regression.} \\ \textbf{Require: Set of poses } \textbf{X} &= \{\textbf{x}_i\}, \text{ Prior weights } \textbf{w}_0 &= \{\textbf{w}_k\} \text{ for local window } \Omega_i \\ \textbf{Ensure: Filtered poses } \textbf{X}^f &= \{\textbf{x}_i^f\} \\ \textbf{X}^f &\leftarrow [\] \\ \textbf{for } \textbf{x}_i &\in \textbf{X} \text{ do} \\ \textbf{X}_{\Omega} &\leftarrow \{\textbf{x}_k\} &\in \Omega_i \\ \textbf{X}_{\Omega} &\leftarrow [\textbf{log}_{\textbf{x}_i}(\textbf{X}_{\Omega}) \\ \textbf{X}_{\Omega}^{proj} &\leftarrow \text{irls.wpca}(\textbf{X}_{\Omega}^t, \textbf{w}_0) \\ \textbf{x}_i^f &\leftarrow \text{exp.}_{\textbf{x}_i}(\textbf{X}_{\Omega}^{proj}(i)) \\ \end{tabular}$

10.50 am Oral Session

 $\mathbf{x}_i^f \leftarrow \exp_{\mathbf{x}_i}(\mathbf{X}_{\Omega}^{\operatorname{proj}}(i))$ $\mathbf{X}^f \leftarrow \mathbf{X}^f \cup \mathbf{x}_i^f$ end for

Algorithm 2 irls.wpca : IRLS for weighted PCA.

Require: Local set of poses $\mathbf{X} = \{\mathbf{x}_i\}$, Kernel size K, Prior weights $\mathbf{w}_i = \{\mathbf{w}_i\}$, i Herations \mathbf{n} , Small δ Ensure: PCA line I with projections $\mathbf{X}^{2\pi i 0}$ $\mathbf{w} \leftarrow \mathbf{w}_0$ $\{\mathbf{X}^{\pi i 0}, \mathbf{I}\} \leftarrow \text{weighted.pcn}(\mathbf{X}, \mathbf{w})$ $\mathbf{w} = \mathbf{I}(\mathbf{w}_i)$ with $\mathbf{w}_i = 1/\text{max}\left\{\delta, \frac{1}{K}\sum_{k=1}^K \left\|\mathbf{x}_i^k - \mathbf{x}_i^k\right\|^{2\pi i 0}\right\}\right\}$ $\mathbf{w} \leftarrow \mathbf{w} \cdot \mathbf{w}_0/\|\mathbf{w} \cdot \mathbf{w}_0\|$ $\Rightarrow \text{Dampen the estimates.}$ end for



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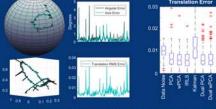
[5] R. Newcombe, I. Shahram, O. Hilliges, D. Molyneaux, D. Kim, A. Davison, P. Kohi, J. Shotton, S. Hodges, A. Fitzgibbon. KinectFusion: Real-time dense surface mapping and tracking. ISMAR 2011.

Our camera poses are calculated via ICP registration only with the depth images. The motion filter is applied afterwards.

Experimental Evaluation

Synthetic Tests

The manifold aware filter methods are tested both with separated translation and quaternion as well as jointly on dual quaternion space and compared to a Kalman filter.

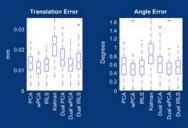


> Dual space formulation robustifies smoothing

Synthetic Tests

Testing is performed on the stereo tracking dataset [4] for natural hand movements in cooperative robotics.

 No dual space gain in case of reliable, accurate poses



Kinect Fusion [5]



Conclusion

- Differential geo. method gives non-parametric smoothing
- Outlier-aware method, no explicit noise model needed
- Dual guaternion formulation robustifies filtering process







