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Target Shape Identification for Nanosatellites using Monocular Point Cloud Techniques

6th European CubeSat Symposium
Oct. 16, 2014

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Overview

1) Basic Concepts
2) Feature Matching & Triangulation
3) Motion Estimation
4) Visual Correspondence
5) Algorithm Results
6) Conclusions
7) Future Directions
CubeSat Vision

- Cubesats of the future will work in close proximities
- Vision: a very well-studied & intuitive sensory method
- Visual ID and tracking can be based on successful ground robotics point cloud methods

Approach and Localize

Tracking and Identification

Ideally <1s per frame!
Structure From Motion (SFM)

- Using one camera and multiple angles, make a 3-D point cloud
- Incremental matching of images used to minimize processing
- Allows combining images from air (e.g. quadcopter) and ground (e.g. rover)
Feature Detection

Features are based on a patch $p$ and many kinds are available:

- SIFT (patented)
- SURF (patented)
- ORB (Oriented BRIEF)

We use ORB (Rublee et al, 2011), with orientation “steering” from

$$F = R_f \begin{pmatrix} a_1 & \cdots & a_n \\ b_1 & \cdots & b_n \end{pmatrix}$$

ORB algorithm uses FAST corners by intensity centroid to speed matches

$$C = \begin{pmatrix} m_{10} & m_{01} \\ m_{00} & m_{00} \end{pmatrix} \quad \text{where} \quad m_{pq} = \sum_{x,y} x^p y^q I(x,y)$$

and BRIEF keypoint descriptors described from intensity $p(a)$ at $a$:

$$\tau(p; a, b) = \begin{cases} 1 & : p(a) < p(b) \\ 0 & : p(a) \geq p(b) \end{cases}$$

$$f_n(p) = \sum_{1 \leq i \leq n} 2^{i-1} \tau(p; a_i, b_i)$$

$$g_n(p, \theta) = f_n(p) \lor (a_i, b_i) \in F$$
Point Cloud Triangulation

- Feature points are matched between successive images with FLANN (Muja & Lowe, 2009)
  \[ M_g = M_f(a) | d_a < d_{max}/2 \]
- Fundamental matrix \( F \) found by least-squares or RANSAC
  \[ a_i^T Fa_i = 0, \ i = 1, \ldots, n \]
- Essential matrix \( E \) is \( F \) with calibration: \( E = K^T FK \)
- Rotation \( R \) and translation \( t \) matrices from SVD of \( E \)
  (Hartley & Zisserman, 2004)
    - 4 Combinations of factorizations:
      \[ R = UW^T V^T \quad R = UWV^T \]
      \[ t = U(0, 0, 1)^T \quad t = -U(0, 0, 1)^T \]
- Least-Squares triangulation finds 3D points by iterative solution
- Locate camera (PnP solution)
- Bundle Adjustment (optional)
Relative Ego-Motion Estimation

- One camera:
  - “Partially-Observable SLAM”
  - “Bearings-Only SLAM”
- 2 images needed for 3-D
- >3 images needed for motion
- If a singular $E$ is obtained, backstep by one more image
- Transform to current position:
  $$C_w(t) = [R_w(t-1)R(t)][(T(t) + T_w(t-1))R(t)]$$
- Then project “real” features as:
  $$x' = (R_w(t-1)R(t))^T x + (T(t) + T_w(t-1))R_w(t-1)$$
- Quaternion obtained as:
  $$Q = \begin{bmatrix} w \\ x \\ y \\ z \end{bmatrix} = \frac{1}{2} \begin{bmatrix} \sqrt{1+r_{00}+r_{11}+r_{22}} \\ r_{21}-r_{12} \\ 2 \sqrt{1+r_{00}+r_{11}+r_{22}} \\ r_{02}-r_{20} \end{bmatrix}$$
  \begin{bmatrix} r_{10}-r_{01} \\ 2 \sqrt{1+r_{00}+r_{11}+r_{22}} \\ r_{02}-r_{20} \end{bmatrix}$$
Correspondence Grouping

- For matching, the normals $N$ of the point cloud are obtained
- A set of keypoints are chosen & given 3D SHOT (Signature of Histograms of Orientations) descriptors $D$ with fixed radius (Salti, Tombari, Stefano, 2014)
- Dot product of $N$: $f(N_p, N_q) = N_p \cdot N_q$
- Generalizes to: $D(p) = \bigcup_{i=1}^{m} SH_{g,f}^i(p)$
- FLANN search again used to find corresponding keypoints in scene
- Clustering is performed by pre-computed Hough voting (Tombari and Stefano, 2010)
  - Model (offline): $V_{i,L}^M = [L_{i,x}^M, L_{i,y}^M, L_{i,z}^M] \cdot (C_i^M - F_i^M)$
  - Scene (online): $V_{i,G}^S = [L_{j,x}^S, L_{j,y}^S, L_{j,z}^S] \cdot V_{i,L}^M + F_j^S$
Correspondence: dense scene

6524 model points, 5584 scene points (from 220 images)

Test 1: Descriptor radius 0.05, cluster size 0.1: 167 points, 63 matches

Test 2: Descriptor radius 0.1, cluster size 0.5: 632 points, 594 matches
Correspondence: sparse scene

6524 scene points, 1816 scene points (from 32 images)

Test 3: Descriptor radius 0.05, cluster size 0.1: 77 points, 28 matches

Test 4: Descriptor radius 0.1, cluster size 0.5: 77 points, 70 matches
### Timing

Time taken in seconds, for 667MHz ARM-Cortex A9 (Xilinx Zynq)

#### Point Cloud Generation (mean time for one pose estimate)

<table>
<thead>
<tr>
<th>Test</th>
<th>Feature Detection</th>
<th>Feature Matching</th>
<th>Feature Selection</th>
<th>Fundamental Matrix</th>
<th>Essential Matrix</th>
<th>Triangulation</th>
<th>PnP RANSAC</th>
<th>Ego-Motion</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-2</td>
<td>0.12</td>
<td>0.058</td>
<td>0.015</td>
<td>0.083</td>
<td>0.0017</td>
<td>0.038</td>
<td>0.0033</td>
<td>0.0005</td>
<td>0.32</td>
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<tr>
<td>3-4</td>
<td>0.12</td>
<td>0.061</td>
<td>0.010</td>
<td>0.048</td>
<td>0.0014</td>
<td>0.025</td>
<td>0.0026</td>
<td>0.0004</td>
<td>0.27</td>
</tr>
</tbody>
</table>

#### Correspondence Grouping (mean time for one correspondence)

<table>
<thead>
<tr>
<th>Test</th>
<th>Model Normals</th>
<th>Scene Normals</th>
<th>Model Sampling</th>
<th>Scene Sampling</th>
<th>Model Keypoints</th>
<th>Scene Keypoints</th>
<th>FLANN Search</th>
<th>Clustering</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.17</td>
<td>0.15</td>
<td>0.027</td>
<td>0.020</td>
<td>1.26</td>
<td>0.84</td>
<td>107.7</td>
<td>0.92</td>
<td>112.1</td>
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<tr>
<td>2</td>
<td>0.17</td>
<td>0.15</td>
<td>0.029</td>
<td>0.024</td>
<td>3.37</td>
<td>2.19</td>
<td>118.0</td>
<td>2.00</td>
<td>127.2</td>
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<tr>
<td>3</td>
<td>0.17</td>
<td>0.043</td>
<td>0.031</td>
<td>0.0083</td>
<td>3.31</td>
<td>0.37</td>
<td>42.5</td>
<td>0.63</td>
<td>48.4</td>
</tr>
<tr>
<td>4</td>
<td>0.17</td>
<td>0.041</td>
<td>0.031</td>
<td>0.0078</td>
<td>3.31</td>
<td>0.37</td>
<td>42.6</td>
<td>1.36</td>
<td>49.1</td>
</tr>
</tbody>
</table>
Discussion of Results

All code written in C++
• ORB Features implemented using OpenCV Libraries
• Correspondence/visualization using Point Cloud Library (PCL)
• Processing is done on a per-pose basis with accumulated points
  – scene is developed over time
  – Slower movement = more poses = more points = higher accuracy
• Increase descriptor sizes =
  – More keypoints found
  – Better accuracy
  – Longer processing time
• Increase cluster sizes =
  – Better matching
  – Slightly higher accuracy
  – Slightly longer processing
• FLANN search for correspondence takes 90% of current processing times
  – High-value candidate for hardware acceleration!
Conclusions

- We have presented one possible set of algorithms for future close-range CubeSat Visual Identification and Tracking
- Accuracy is good, small improvements would enable capture
- Feature Detection and Point Cloud Generation is (barely) tractable, and could be accelerated further
- Correspondence Grouping is currently intractable due to keypoint searching and to a lesser extent, keypoint generation
  - Hardware acceleration for FLANN & keypoints may help

Critical factors for good results:
- Sharpness of image
  - good focusable optics
  - light field cameras?
- Consistency of exposure
  - automate, or post-process linearized image
- Speed of processing
  - frequent frame updates are essential for SLAM methods
DSP-Based Vision System

- Board based on open designs of Surveyor SRV-1 and LeanXCam
- ADI Blackfin BF537 DSP provides optimized fixed-point processing

- Initial tests done on BF537-Stamp board
- OpenCV and FOSS code used for testing
  - fixed point code needed
  - fast, limited in resolution
FPGA-Based Vector Processing
Thank You!

Any Questions?

Dense reconstruction courtesy of C. Wu's VSFM and Y. Furukawa's CMVS