Tightly-Integrated Visual and Inertial Navigation for Pinpoint Landing on Rugged Terrains

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Summary

1. Motivation & System Overview
2. Mapped Landmark Matching
3. Filtering & Data Fusion
4. Simulation & Results
5. Conclusion & Future Work
6. Questions
Motivation

• Planetary landing mission needs:
  – Autonomy
    • Robust to communication link failures and no delays
  – Accuracy
    • Sites of scientific interest
    • Previously-landed assets: rover, astronauts, etc.
    • Technical requirements about the area: illumination patterns, hazard presence, etc.

• Navigation sensors:
  – Terrain sensors for precision: LiDAR or camera
    ✓ Lightweight, cheap, high TRL, passive (operates from any distance)
    ✗ Needs illumination, 2D (only) image measurements

• Constraints: Many sites have complex non-flat topographies.

• PhD objectives: Vision-based navigation system
  – Orbit-to-touchdown operations capable of a 100-m landing accuracy
  – Rugged-terrains capable
  – Validation: lunar landing software simulation, UAV real-time implementation
System Overview

- **Image data fused with an Inertial Measurement Unit (IMU)**
  - Measures non-gravitational accelerations and angular rates
  - High-frequency estimation, continuous navigation when camera fails, solves visual scale problem
- **Matching of online image features with mapped landmarks**
  - IMU biases estimation and error-drift correction
- **Tight fusion scheme**
### Absolute Image Referencing Methods

**Matching type** | **Method** | **Advantages** | **Drawbacks** |
|------------------|------------|----------------|---------------|
| **Patch correlation** | Raw-image correlation  
(Conte and Doherty, 2009) | - Proven real-time efficiency | - Memory requirement  
- Illumination sensitivity  
- Attitude error sensitivity  
- Relief sensitivity |
| | Rendered-image correlation  
(Adams et al., 2008) | - All modeled disturbances are counted in  
- Relief handled | - Processing requirement  
- Memory requirement  
- State estimates needed |
| | Reconstructed-DEM matching  
(Jansche, 2006) | - Relief can be handled | - Memory requirement  
- Correlator hardware needed |
| | FFT + warped image correlation  
(Mourikis et al., 2006) | - Proven real-time efficiency  
- Accurate | - Illumination sensitivity  
- Relief-sensitive |
| **Intensity signatures** | SIFT (Lowe, 2004) / SURF (Bay et al., 2008) | - Scale and rotation invariance  
- Low memory requirement  
- Relief-sensitive | - Computationally expensive  
- Illumination-sensitive |
| **Geometric signatures** | Conics invariant  
(Cheng and Anear, 2005) | - No state estimate needed  
- Illumination robustness  
- Low memory requirement | - Only with craters  
- Planar terrain assumed |
| | Projected virtual landmark  
(Singh and Lim, 2008) | - Illumination robustness  
- Low memory  
- Relief handled  
- Any type of landmark | - State estimates needed  
- False matches |
| | Landmark constellation matching  
(Pham et al., 2009) | - Illumination robustness  
- Low memory  
- Any type of landmark | - Planar terrain assumed  
- Attitude and attitude estimates needed |

- **Global image or reconstructed-DEM correlation:**
  - **X** Map memory size

- **Local patch correlation, SIFT/SURF:**
  - **X** Illumination-sensitive

- **Craters conic-invariant:**
  - **X** Only for craters

- **2 methods selected:**
  - ✓ Project landmarks
  - ✓ Landstel
Data fusion alternatives

• Numerical approximations of Kalman filtering extended to non-linear system and measurement model: EKF

• Loose fusion: state measurements
  ✓ Computational cost
  ✓ Redundancy
  X Precision
  X Stability

• Tight fusion: direct image measurements
  ✓ Precision
  ✓ Robustness
  X Implementation
  X Computational cost
Matching process

• Inputs:
  – Online image
  – Position and attitude estimates from the filter
  – On-board map

• Outputs: Image (2D) / World (3D) landmark coordinates matches

• Method:
  1. Projection of the 3D map points onto the estimated focal plane
  2. Signature extraction on both the online and predicted image
  3. RANSAC-based robust matching

• On-board map: 3D model of surface feature points
  – Extraction from an orbital image using a corner detector (e.g. Harris)
  – 3D coordinates retrieved by interpolation from a DEM the same area
  ➔ On-board data: 3xN matrix
Projection and pre-matching steps

- **3D model projection:**
  - Current camera pose estimated from the filter
  - Known camera calibration model
  - On-board map
  ➔ 2D feature coordinates prediction

- **Potential matches like Landstel (Pham et al., 2009): Shape Context**
  - Feature point characterized by the geometric distribution of its neighbours
    - Minimum and maximum distances: \( b_r \) and \( p_r \)
    - Distance and polar angle
    - Histogram signatures counting neighbours in each quadrant
  - One-to-one signature comparison
    - Distance criterion based on \( \chi^2 \) distance
    - Selection cut for distances lower than a threshold
  ➔ Set of potential matches BUT:
    - Many outliers
    - Several candidates for each image features
RANSAC-based robust matching

- **RANSAC**: RANdom SAmple Consensus (Fischler et al., 1981)
  - Outliers removal by fitting a model to experimental data
- **Model**: calibrated camera pose (Fischler et al., 1981)
  - Closed-form solution from 3 matches
  - 4 possible solutions: that closest to the filter estimate is selected

- **Algorithm**
  - Inputs: (2D,3D) potential matches
  1. Select a random set $s$ of 3 potential matches
  2. Degenerate configuration check
  3. Compute the associated camera solution
  4. Determine the inliers
  5. If $\#\{\text{inliers}\}>T_0$, store the inlier vector
  6. Back to step until max. number of iterations is reached
  - Outputs:
    - Camera model having most inliers
    - Corresponding inliers $\Rightarrow$ Fed to the filter
Discussion

• Comparison with projected landmarks method (Singh et al., 2008):
  - Same on-board map and matching geometric space (focal plane)
  - No outlier removal step
    • Closest-distance criterion
    • No match when filter has not converged properly
  
  Note: RANSAC is a proven real-time technique in terrestrial robotics.

• Comparison with Landstel (Pham et al., 2008):
  - Same signature and pre-matching method
  - Different outlier removal step
  - Different matching geometric space: horizontal plane in Landstel
    • Flat-world assumption in Landstel struggling on rugged terrains (relief > 10% altitude)
  - Signature extraction only needed in the online image in Landstel
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Filter block and system model

- Inputs/Outputs:
  - Vehicle state: \( \mathbf{x}_V = \begin{bmatrix} \mathbf{q}_{gb}^T & \mathbf{b}_{gb}^T & \mathbf{v}_{gb}^T & \mathbf{b}_{gb}^T & \mathbf{p}_{gb}^T \end{bmatrix}^T \)

- System model:
  \[
  \begin{bmatrix}
  b \\
  \mathbf{q}_g = \frac{1}{2} \Omega(\mathbf{\omega}_{gb}) \mathbf{q}_g \\
  \mathbf{b}_{gb} = \mathbf{n}_{gb} \\
  \mathbf{v}_{gb} = \mathbf{a}_{gb} \\
  \mathbf{b}_{gb} = \mathbf{n}_{gb} \\
  \mathbf{p}_{gb} = \mathbf{v}_{gb}
  \end{bmatrix}
  \quad
  \Omega(\mathbf{\omega}) = \begin{bmatrix} 0 & -\mathbf{\omega}^T \\ \mathbf{\omega} & -[\mathbf{\omega} \times] \end{bmatrix},
  \quad
  [\mathbf{\omega} \times] = \begin{bmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{bmatrix}
  \]

- IMU:
  \[
  \mathbf{\omega}_{NRI} = \mathbf{\omega}_{gb} + C(\mathbf{q}_g^b)(\mathbf{\omega}_g) + \mathbf{b}_{gb} + \mathbf{n}_{gb}
  \quad
  \mathbf{a}_{AMU} = C(\mathbf{q}_g^b)(\mathbf{a}_{gb} - \mathbf{\omega}_g^b + 2[\mathbf{\omega}_g] \mathbf{v}_{gb} + [\mathbf{\omega}_g \times] \mathbf{p}_{gb}^b) + \mathbf{b}_{gb} + \mathbf{n}_{gb}
  \]
State & covariance propagation

- **State propagation:**
  - Expectation operator applied to $\mathbf{x}_V = f(\mathbf{x}_V, \mathbf{n}_{IMU})$

  $\hat{\mathbf{q}}_g = \frac{1}{2} \Omega(\hat{\mathbf{\omega}}) \mathbf{q}_g$

  $\hat{\mathbf{b}}_{avr} = 0_{3 \times 1}$

  $\hat{\mathbf{\nu}}_{gb} = C(\mathbf{q}_g^b)^T \mathbf{a} - 2 [\mathbf{\omega}_{gb}^g \wedge] \mathbf{v}_{gb}^g - [\mathbf{\omega}_{gb}^g \wedge]^2 \mathbf{p}_{gb}^g + \mathbf{g}_b^g$

  $\hat{\mathbf{b}}_{avr} = 0_{3 \times 1}$

  $\hat{\mathbf{p}}_{gb} = \mathbf{v}_{gb}^g$

  with $\mathbf{a} = \mathbf{a}_{IMU} - \hat{\mathbf{b}}_{avr}, \mathbf{\omega} = \omega_{IMU} - \hat{\mathbf{b}}_{avr} - C(\hat{\mathbf{q}}_g^b)\mathbf{\omega}_{gb}^g$

- **Covariance propagation**
  - EKF: Linearization wrt state estimate $\delta \mathbf{x}_V = \mathbf{x}_V - \hat{\mathbf{x}}_V$

    $\delta \mathbf{x}_V = \mathbf{F}_V \delta \mathbf{x}_V + \mathbf{G}_V \mathbf{n}_{IMU}$

    $\delta \mathbf{x}_V = \begin{bmatrix} \delta \mathbf{\theta}_g^T & \delta \mathbf{b}_{gvr}^T & \delta \mathbf{v}_{gb}^T & \delta \mathbf{b}_{avr}^T & \delta \mathbf{p}_{gb}^T \end{bmatrix}$

  - Propagated covariance:

    $\mathbf{P} = \begin{bmatrix} \mathbf{P}_V & \mathbf{P}_{correlation} & \mathbf{P}^T_{correlation} & \mathbf{P}_{previous} \end{bmatrix}$

    $\Rightarrow$ State management
State management

- New image ➔ State augmentation
- Previous camera pose is stored in memory ➔ Processing delays are accounted for.
• Mapped Landmark Matching output:
  – Image 2D coordinates \((z_j)_j\) ✧
  – Associated world 3D landmark coordinates: \((p^R_{rlj})_j\) ✧

\[
\begin{align*}
  z_j &= h_j(x) + n_j = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} p^c_{rl} + n_j \\
  \hat{z}_j &= C(q_x') (p^q_{rl} - \hat{p}^q_{avl}) + C(q_x') (p^q_{rl} - \hat{p}^q_{avl})
\end{align*}
\]

– Linearization wrt image prediction

\[
\delta z_j = H_j \delta x + \delta n_j = H_j \delta \theta_x^{c-1} + H_j \delta p_{avl}^q + n_j \quad \text{with} \quad \delta z_j = z_j - \hat{z}_j
\]

⇒ Allows Kalman gain to be computed for EKF update
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Simulation environment

- **Virtual terrain points mesh:**
  - Random uniform horizontal and vertical distribution
  - Altitude range can be varied to account for different topographies.

- **Trajectory selected: Moonlanding approach phase**
  - Duration: 80 seconds, 2-km altitude and 65 m/s velocity at startup
  - Guidance is based on that of Apollo LM

- **Matlab Simulink IMU model calibrated to match performances of state-of-the-art IMUs.**

- **Image: terrain points projection**
  - Focal plane placed using true pose from simulator.
  - Noise: $\sigma_{\text{im}} = 1$ pixel
  - 1024X1024 image spanning 70 deg FoV
• Number of terrain points: 505
• Not enough points visible at low altitudes ⇔ Low orbital image resolution
  1. Visual phase: state updates happen
  2. Inertial phase: drift due to error integration
Navigation performance

- 3σ initial uncertainty: 1 deg, 10 m/s, 100 m per axis
  - Rather conservative for a lunar approach phase starting at a 2-km altitude.

### Attitude

#### Time [s]

- Roll angle
- Pitch angle
- Yaw angle

### Velocity

#### Time [s]

- X-velocity error [m/s]
- Y-velocity error [m/s]
- Z-velocity error [m/s]

### Position

#### Time [s]

- X-position error [m]
- Y-position error [m]
- Z-position error [m]
Terrain relief sensitivity

- Sensitivity to terrain topography:

<table>
<thead>
<tr>
<th>Surface altitude range (m)</th>
<th>Position error after visual phase (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>20.9</td>
</tr>
<tr>
<td>100</td>
<td>19.0</td>
</tr>
<tr>
<td>200</td>
<td>20.1</td>
</tr>
<tr>
<td>1000</td>
<td>20.4</td>
</tr>
</tbody>
</table>

- Terrain elevation variation up to half the initial altitude have no influence on performance
  - First proof of concept
  - Further development on images with new issues: occlusions, etc.
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Conclusion

• Tightly-integrated fusion approach between
  – An IMU
  – Absolute image measurements of mapped landmarks

• 3σ position error < 100 m after visual phase

• Performances independent of terrain topography
  ➔ Candidate solution for pinpoint landing navigation on rugged terrains

• Future work:
  – Monte Carlo analysis to check robustness
  – Testing on an orbit-to-touchdown trajectory
  – Testing with images
  – Relative feature processing: limiting drift at low altitudes
  – Compare EKF with UKF and PF.
Questions?

References: Fischler et al., 1981, *Communications of the ACM*, 24

Pham et al., 2009, in *AIAA Guidance, Navigation and Control*

Singh et al., 2008, in *AIAA Guidance, Navigation and Control Conference and Exhibit*
Lunar South Pole Topography

Backscatter image of the lunar south pole region obtained by the GSSR after correcting for the antenna pattern.

(From: Hershey, S., E. Garcelo, P. Rosen, M. Stiefe, J. Jiao, M. Kobrick, B. Wilson, C. Chen, and R. Jurgens,
"An Improved Map of the Lunar South Pole with Earth Based Radar Interferometry."
from: RadarCon2009 Special Issue, to be published in IEEE Radar, Sonar, and Navigation journal.)