Title

Visual-inertial Motion Estimation for Accurate Localization, Mapping and Environment Sensing

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Visual-Inertial Motion Estimation

for Accurate Localization, Mapping and Environment Sensing

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Introduction: Accurate Mapping and Environment Sensing

Research Goals

- **Accurate mapping and observation of wide-scale spatiotemporal phenomena.**
  - This task demands exact knowledge of *where* the sensor is positioned in space.
- **Precise localization of a *moving* sensor platform.**
  - Fusing observations from a moving platform requires precise and reliable localization.

Challenges and Approach

- **Performance is sensor-dependent.**
  - Global localization is possible using sensors such as GPS, but requires line of sight to GPS satellites - this is not always available, especially when operating under forest canopy.
  - Many other possible sensor choices - depends on the particular application.
- **We use stereo cameras and an Inertial Measurement Unit (IMU).**
  - Passive sensors, which do not radiate energy into the environment.
  - Complementary - each compensates for weaknesses in the other.

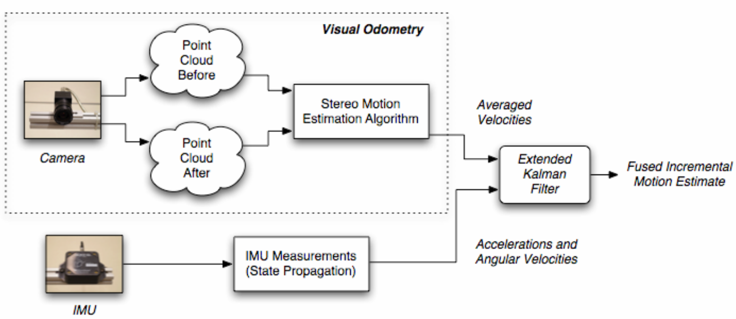
The Question: How can we accurately and reliably localize a moving sensor platform?

Using Visual and Inertial Motion Estimation

- **Applicable to a wide range of platforms, from high-speed aerial and ground robots to low-speed actuated sensor nodes.**
  - We test our algorithms on AVATAR, an autonomous unmanned aerial vehicle.
  - A very challenging estimation problem. Helicopter can move rapidly in all 6-DOF.
  - Vehicle flies close to the ground - camera images change quickly.

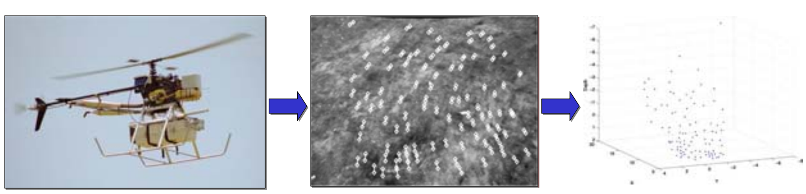
Method and Results: Motion Estimation Using Stereo Vision and Inertial Sensing

System Block Diagram

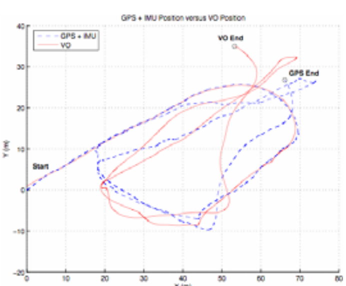


Motion Estimation Algorithm

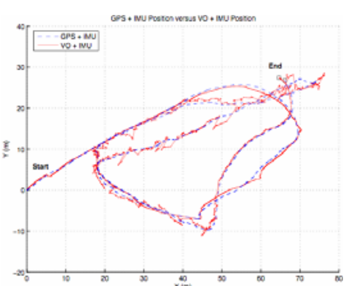
1. **Track point features across sequential left camera images.**
2. **Match features in right stereo image with normalized cross-correlation.**
3. **Triangulate landmark positions in 3D, and compute covariances.**
4. **Filter landmark points to remove outliers due to incorrect data associations.**
5. **Compute visual pose change estimate using iterated nonlinear least-squares.**
6. **Fuse visual estimate with integrated data from IMU, using an Extended Kalman Filter (EKF).**



Motion Estimation Results



Motion estimate using Visual Odometry alone. 14.7 meter error over 405.5 meters.



Motion estimate using VO and IMU data. 1.6 meter error over 405.5 meters.