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Open Keyframe-based Visual-Inertial SLAM

Keyframe-Based Visual-Inertial Odometry Using Nonlinear Optimization

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- Introduction
- Notation and Definitions
- Methodology
- Results and Evaluation
- Conclusion

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- **Introduction**
  - **Introduction to Visual-Inertial Odometry**
  - **Challenges in Visual-Inertial Fusion**
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Introduction to Visual-Inertial Odometry

- VIO
- Approaches
- Advantages of Batch Approaches
- Tightly-Coupled vs. Loosely-Coupled Systems
- Paper's Focus and Contributions

Introduction to Visual-Inertial Odometry

- **VIO**
  - Visual-Inertial Odometry (VIO) combines visual data (from cameras) and inertial measurements (from IMUs).
  - Essential for robust and accurate localization and mapping in mobile robotics.
- **Approaches**
- **Advantages of Batch Approaches**
- **Tightly-Coupled vs. Loosely-Coupled Systems**
- **Paper's Focus and Contributions**

Introduction to Visual-Inertial Odometry

- **VIO**
- **Approaches**
  - Two main methods: batch nonlinear optimization and recursive filtering.
  - Batch methods minimize error from IMU measurements and visual terms.
  - Recursive algorithms use IMU for state propagation and updates from visual observations.
- **Advantages of Batch Approaches**
- **Tightly-Coupled vs. Loosely-Coupled Systems**
- **Paper's Focus and Contributions**

Introduction to Visual-Inertial Odometry

- **VIO**
- **Approaches**
- **Advantages of Batch Approaches**
  - Offer repeated linearization, limiting errors.
  - Historically limited by computational resources, now viable for real-time operation.
- **Tightly-Coupled vs. Loosely-Coupled Systems**
- **Paper's Focus and Contributions**

Introduction to Visual-Inertial Odometry

- **VIO**
- **Approaches**
- **Advantages of Batch Approaches**
- **Tightly-Coupled vs. Loosely-Coupled Systems**
  - Tightly-coupled systems integrate IMU and camera measurements into a common problem.
  - Loosely-coupled systems estimate pose independently and fuse IMU data separately.
  - Tightly-coupled approaches show higher accuracy in high precision VINS.
- **Paper's Focus and Contributions**

Introduction to Visual-Inertial Odometry

- **VIO**
- **Approaches**
- **Advantages of Batch Approaches**
- **Tightly-Coupled vs. Loosely-Coupled Systems**
- **Paper's Focus and Contributions**
  - Advocates tightly-coupled fusion and nonlinear optimization.
  - Develops a probabilistic cost function combining visual and inertial terms.
  - Emphasizes real-time operation, robustness, and accuracy.

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Challenges in Visual-Inertial Fusion

- Evolution from Filtering to Optimization
- Sparsity and Computational Efficiency
- Loosely vs. Tightly-Coupled Systems
- Keyframe Approach

Challenges in Visual-Inertial Fusion

- **Evolution from Filtering to Optimization**
  - Shift from filtering methods to nonlinear optimization for real-time operation and accuracy.
- **Sparsity and Computational Efficiency**
- **Loosely vs. Tightly-Coupled Systems**
- **Keyframe Approach**

Challenges in Visual-Inertial Fusion

- **Evolution from Filtering to Optimization**
- **Sparsity and Computational Efficiency**
    - Emphasis on maintaining structural sparsity in problems for computational efficiency.
- **Loosely vs. Tightly-Coupled Systems**
- **Keyframe Approach**

Challenges in Visual-Inertial Fusion

- **Evolution from Filtering to Optimization**
- **Sparsity and Computational Efficiency**
- **Loosely vs. Tightly-Coupled Systems**
  - Trends towards tightly-coupled systems for exploiting full sensor potential.
  - Challenges in managing computational complexity in tightly-coupled systems.
- **Keyframe Approach**

Challenges in Visual-Inertial Fusion

- **Evolution from Filtering to Optimization**
- **Sparsity and Computational Efficiency**
- **Loosely vs. Tightly-Coupled Systems**
- **Keyframe Approach**
  - Adoption of keyframes for sparsity preservation.
  - Balancing real-time performance with the benefits of re-linearization.

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  - States and Measurements
  - Error State Representation
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Coordinate Frames and Transformations

- **Reference frames:**
  - camera (*C*)
  - world (*W*)
  - IMU (*S*)
- **Homogeneous transformations and rotation matrices between frames**

Coordinate Frames and Transformations

- **Reference frames:**
- **Homogeneous transformations and rotation matrices between frames**

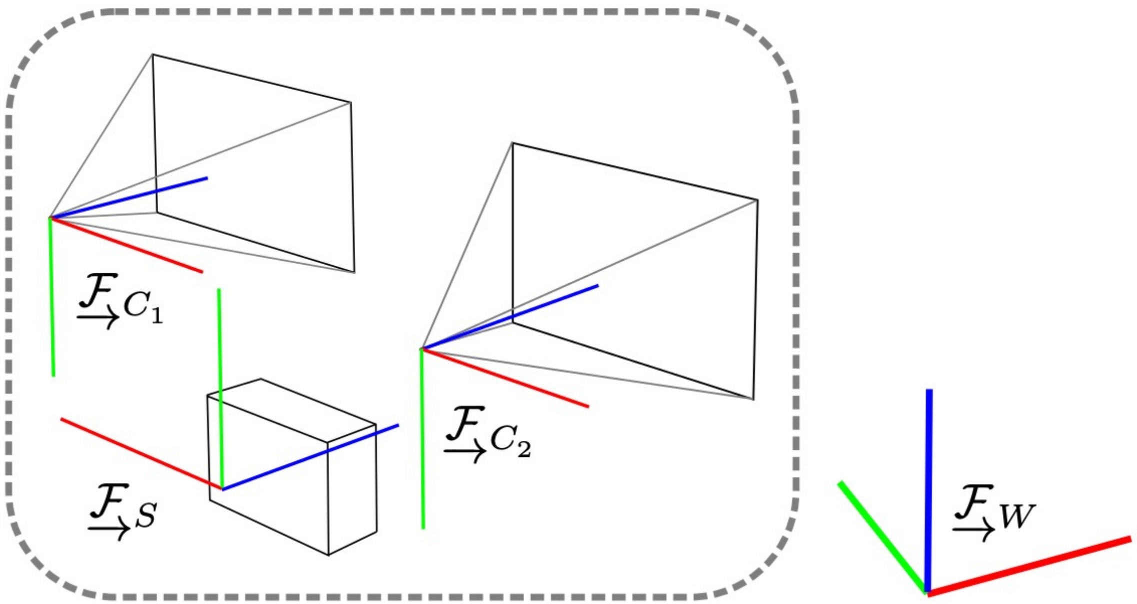

Fig. 2. Coordinate frames involved in the hardware setup used: two cameras are placed as a stereo setup with respective frames, $\underrightarrow{\mathcal{F}}_{C_i}, i \in \{1, 2\}$. IMU data is acquired in $\underrightarrow{\mathcal{F}}_{S}$. The algorithms estimate the position and orientation of $\underrightarrow{\mathcal{F}}_{S}$ with respect to the world (inertial) frame $\underrightarrow{\mathcal{F}}_{W}$.

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States and Measurements

- **Robot state variables**
  - Position
  - Orientation (quaternions)
  - Velocity
  - Gyro biases
  - Accelerometer biases
- **Robot’s state at timestamp**
- **Landmark representation**

States and Measurements

- Robot state variables
- Robot's state at timestamp

$$\mathbf{x}_{\mathrm{R}} := \left[{}_{W}\mathbf{r}_{S}{}^{T}, \mathbf{q}_{WS}^{T}, {}_{S}\mathbf{v}^{T}, \mathbf{b}_{\mathrm{g}}^{T}, \mathbf{b}_{\mathrm{a}}^{T} \right]^{T} \in \mathbb{R}^3 \times S^3 \times \mathbb{R}^9$$

- Landmark representation

States and Measurements

- Robot state variables
- Robot’s state at timestamp
- Landmark representation

$$\mathbf{x}_{\mathrm{L}^j} := {}_{W}\boldsymbol{l}^j \in \mathbb{R}^4$$

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Error State Representation

- Use of minimal coordinates for representing perturbations and error states.
- Linearization around the current state for error propagation.
- Reprojection error

$$\mathbf{e}_{\mathrm{r}}^{i,j,k} = \mathbf{z}^{i,j,k} - \mathbf{h}_i \left(\boldsymbol{T}_{C_i S}^{k} \, \boldsymbol{T}_{SW}^{k} \, {}_{W}\boldsymbol{l}^{j} \right)$$

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Keyframe Selection and Optimization

- **Keyframe Selection**
  - Chosen based on significant changes in viewpoint or scene content to reduce computational load while capturing essential data.
- **Nonlinear Optimization**
- **Sparsity Preservation**

Keyframe Selection and Optimization

- Keyframe Selection
- **Nonlinear Optimization**
  - Iteratively refines the trajectory and map estimates by minimizing the combined reprojection and inertial errors.
- **Sparsity Preservation**

Keyframe Selection and Optimization

- **Keyframe Selection**
- **Nonlinear Optimization**
- **Sparsity Preservation**
  - Keyframes and landmarks maintain a sparse representation, crucial for real-time processing.

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State Estimation and Error Minimization

- **State Vector**
  - Encompasses the robot's position, orientation, velocity, and sensor biases.
- **Reprojection Error**
- **IMU Error Term**

State Estimation and Error Minimization

- **State Vector**
- **Reprojection Error**
  - Measures the discrepancy between observed and predicted landmark positions in image frames, pivotal for map refinement.
- **IMU Error Term**

State Estimation and Error Minimization

- **State Vector**
- **Reprojection Error**
- **IMU Error Term**
  - Accounts for the difference between predicted and observed sensor readings, enhancing motion estimation accuracy.

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  - Data and Metrics for Evaluation
  - Quantitative Performance Results
  - Comparative Results and Discussion
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Data and Metrics for Evaluation

- **Datasets:**
  - Utilized custom-built stereo visual-inertial hardware across various indoor and outdoor settings.
- **Metrics:**
  - **Trajectory Accuracy:** Measured as the deviation from ground truth.
  - **Map Precision**: Assessed by the fidelity of 3D landmark positions.
  - **Computational Performance:** Evaluated by the algorithm's execution time and resource usage.

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Quantitative Performance Results

- **High Precision**
  - Demonstrated superior trajectory tracking with reduced drift compared to benchmarks.
- **Robustness in Diverse Conditions**
  - Maintained performance across different environments and motion dynamics.
- **Efficiency**
  - Achieved real-time operation, with processing times suitable for on-board implementation.

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Comparative Results and Discussion

- **Benchmark Comparison**
  - Outperformed existing methods in accuracy and robustness, with detailed statistics.
- **Stereo vs. Monocular**
  - Showed the benefits of stereo configuration for depth perception and error minimization.
- **Algorithm Improvements**
  - Highlighted significant advancements in handling rapid movements and low-texture environments.

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