MICHIGAN ENGINEERING
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iLoco: Real-Time Visual SLAM using an iPhone

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Agenda

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2. Our Approach
3. Data Collection
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5. Visual Odometry
6. Loop Closure
7. GTSAM
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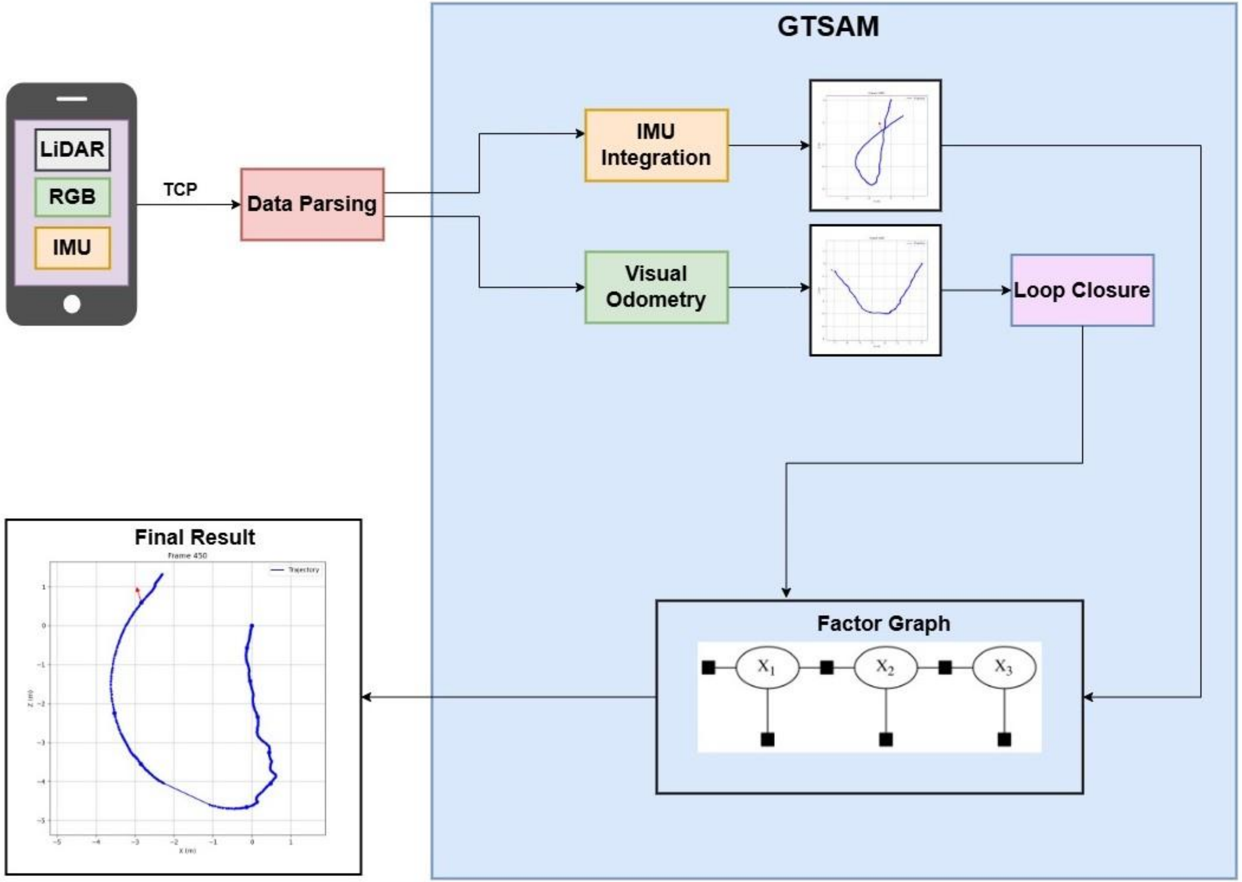
Overview

iLoco: Real-Time SLAM on iPhone

- Traditional SLAM systems often require specialized hardware and complex calibration
- New Smartphones, especially iPhones, offer powerful sensors
- Leverages iPhone’s built-in RGB-D camera and IMU for accurate, real-time localization
- Uses ORB feature matching, Bag-of-Words, GTSAM for our pipeline
- “Slap on” design: minimal setup, no external calibration required
- Ideal for:
    - Rapid prototyping
    - Educational demos
    - Accessible SLAM research

Our Approach



Data Capture

Swift App on iPhone

- Captures RGB + Depth via AVCapture APIs
- Depth and RGB tightly synchronized using AVCaptureDataOutputSynchronizer

Inertial Data via CoreMotion

- Accelerometer + Gyroscope at **100 Hz**
- Timestamped and aligned with visual stream

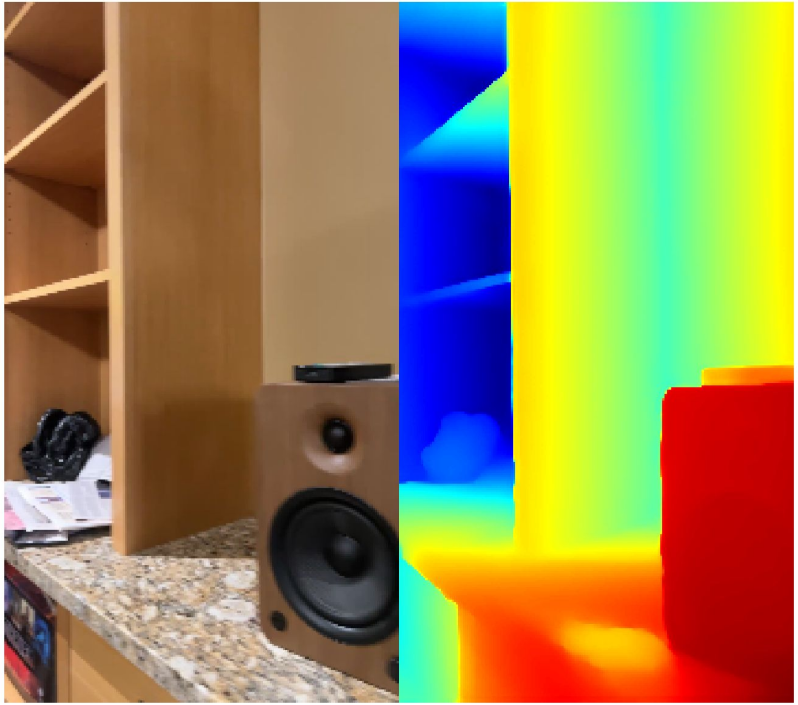
Dual TCP Streaming Architecture

- IMU streamed at 100 Hz
- RGB-D streamed at 30 FPS (H.264 encoded)
- Separate channels reduce packet delay and jitter

Latency-Optimized Design

- H.264 video compression done on iPhone
- Python server decodes stream in real time
- Supports efficient, live SLAM processing

RGB (Left) and Depth (Right) Frames



IMU Odometry

Timestamped IMU Data

- Collected accelerometer & gyroscope readings at 100 Hz
- Data aligned with RGB-D stream for fusion

Rotation Updates via Angular Velocity

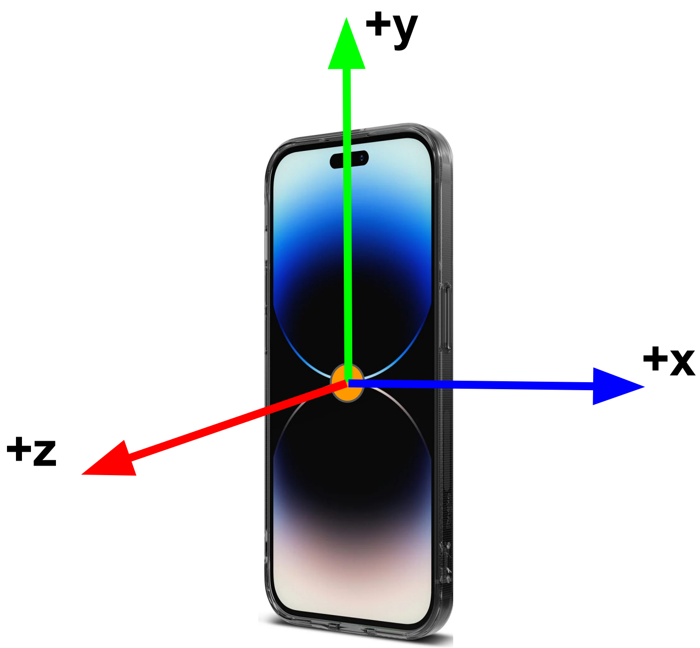
- Skew-symmetric matrix + Rodrigues' formula
- Small-angle approximation with Taylor expansion
- Exponential map applied to angular velocity for rotation matrix

State Propagation

- Discrete-time integration with Zero-Order Hold assumption
- Constant acceleration & angular velocity assumed between frames
- Velocity and position updated from integrated accelerations

Bias-Corrected Integration

- Gyro and accelerometer biases compensated
- Results in smooth, real-time pose estimation



Visual Odometry

Feature Detection

- RGB frames + depth maps captured via iPhone's camera + LiDAR
- ORB keypoints + binary descriptors computed per frame

Feature Matching

- Matched with FLANN (LSH indexing)
- Lowe's ratio test filters unreliable matches

3D Projection from Depth

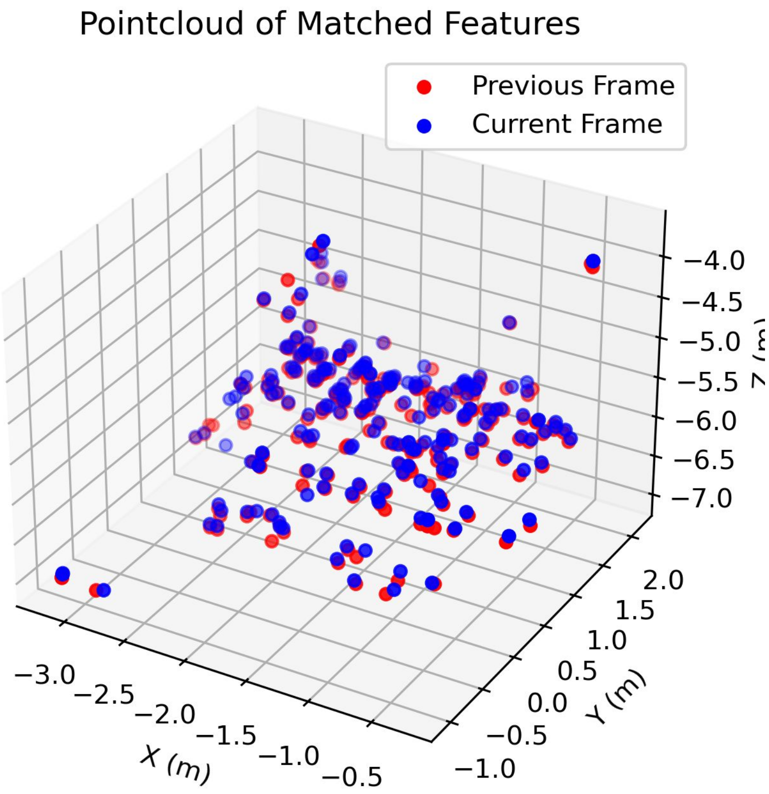
- Depth + camera intrinsics → 3D point cloud
- Only valid depth pixels retained

Pose Estimation

- RANSAC filters outliers
- Rigid transform computed via SVD

Trajectory Accumulation

- Transformations chained over time
- Produces full 6-DoF trajectory in global frame



Loop Closure

Bag-of-Words with ORB

- Visual vocabulary trained from ORB descriptors
- New frames converted into compact BoW vectors

Efficient Candidate Search

- BoW vectors stored in a KD-Tree
- Compared using cosine similarity
- Thresholded to find loop candidates

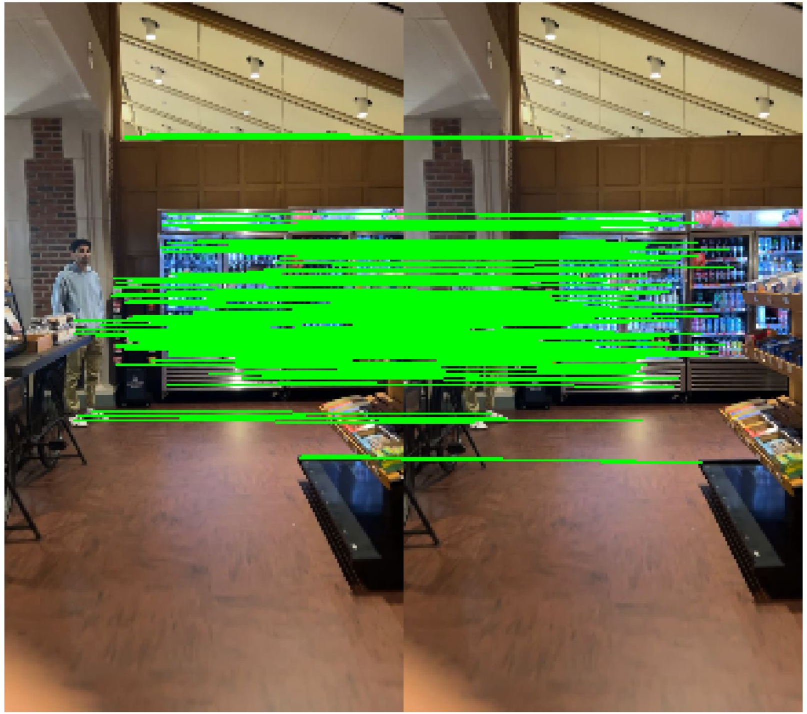
Verification via ORB Matching

- Feature-level validation of candidates
- Loop accepted if enough reliable matches found

Challenges

- Noisy VO/IMU data
- Short runtime limited loop closure effectiveness

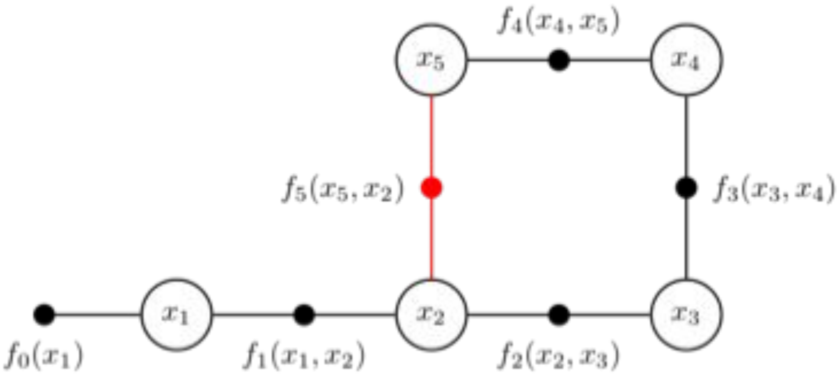
Feature Matches



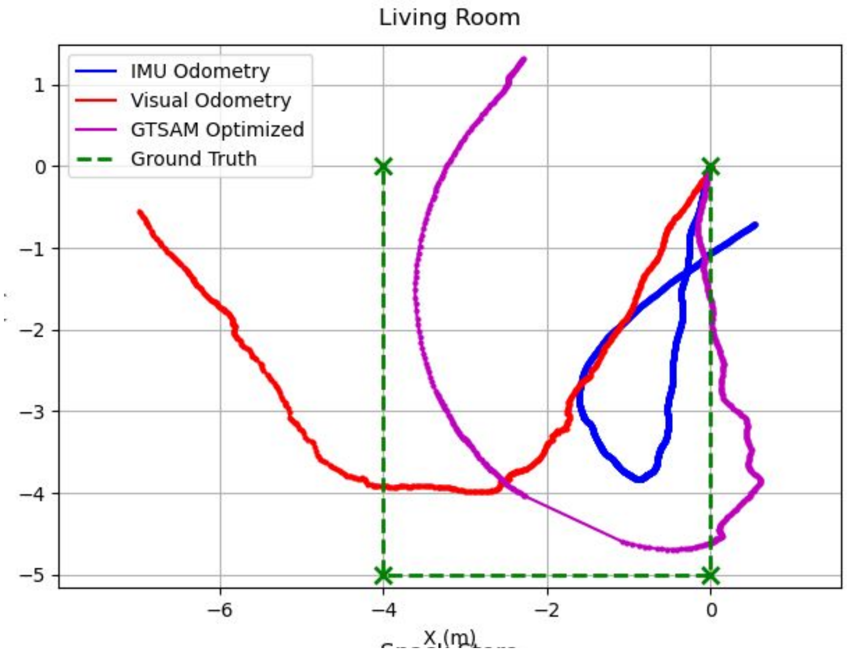
Loop Closure between Frame 150 (left) and frame 12 (right)

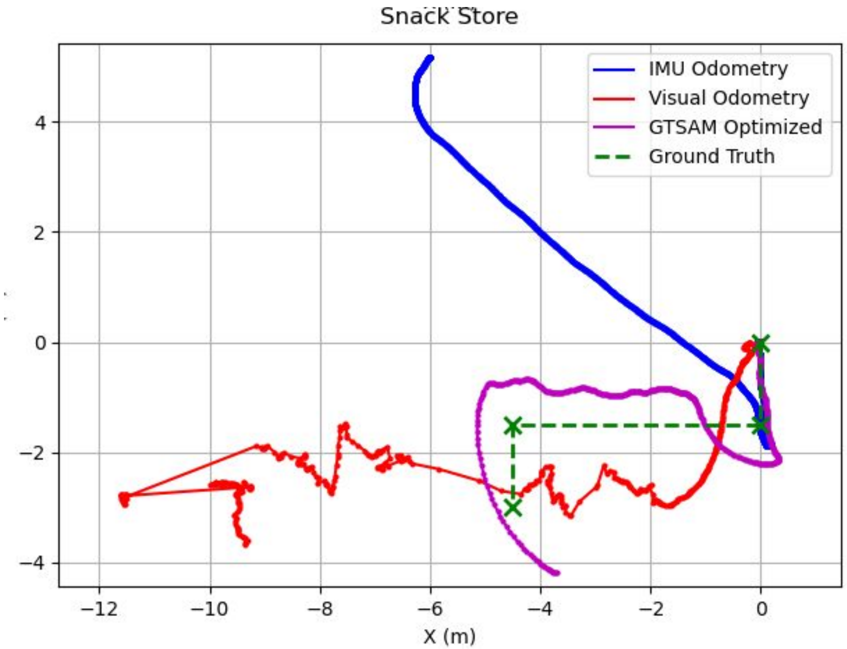
GTSAM

- Performs batch SLAM by combining IMU preintegration with visual odometry
- Builds a factor graph:
  - IMU provides high-frequency motion constraints between keyframes
  - Visual odometry supplies relative pose constraints
- Uses ISAM2 for efficient incremental optimization
- Fuses multi-rate, multi-modal data into a globally consistent trajectory
- Incorporates motion priors and sensor noise models for robustness
- Produces smooth, drift-reduced pose estimates
- Backbone for evaluating downstream video alignment and trajectory prediction



Results


Living Room
IMU Odometry
Visual Odometry
GTSAM Optimized
Ground Truth
1
0
−1
−2
−3
−4
−5
−6
−4
−2
0
X (m)


Snack Store
IMU Odometry
Visual Odometry
GTSAM Optimized
Ground Truth
4
2
0
−2
−4
−12
−10
−8
−6
−4
−2
0
X (m)

More Results

- Measure error as MSE in Lie Group over time

Time (s)	IMU Odometry (Avg ± SD) [m^2]	Visual Odometry (Avg ± SD) [m^2]	Our Method (Avg ± SD) [m^2]
10	0.405 ± 0.075	0.281 ± 0.018	0.292 ± 0.732
20	1.632 ± 0.075	0.541 ± 0.243	0.56 ± 0.332
30	4.542 ± 0.195	1.27 ± 2.549	1.168 ± 1.352
40	8.988 ± 0.465	3.485 ± 1.162	2.14 ± 1.192
50	13.824 ± 1.485	6.13 ± 13.503	3.296 ± 2.088
60	18.6 ± 2.985	7.854 ± 6.778	4.024 ± 2.136

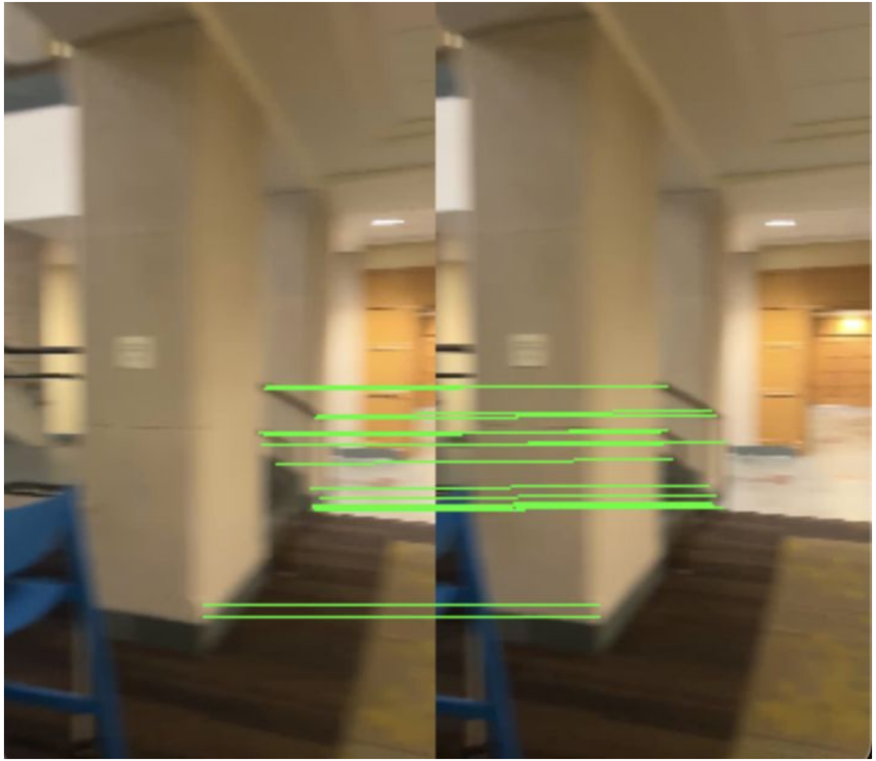
Conclusion

- **Visual Odometry:** Performs poorly during turns, especially in low-texture environments like plain walls.

- **GTSAM Optimization:** Mini-batch updates improve stability and convergence without full batch costs.

- **iLoco vs Baselines:** Our fused method outperforms standalone IMU/VO but lags behind ARKit in rotation accuracy.

- **Future Work:** Add mapping for loop closure and integrate visual and depth data (e.g., LiDAR) separately for better robustness.



Thank You!