Detection and Resolution of Motion Conflict in Visual Inertial Odometry

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1 ABSTRACT

- Similar to human motion sickness, **Motion Conflict** is the disagreement between measurements in a multi-sensor device.
- We present Motion-Conflict aware Visual Inertial Odometry (MC-VIO) algorithm that combines detection and resolution.
- Motion conflict is described using a hidden Markov model with additional states.
- Experimental results show that our method reduces the increase in absolute tracking error by 80% for real-life scenes with motion conflict.

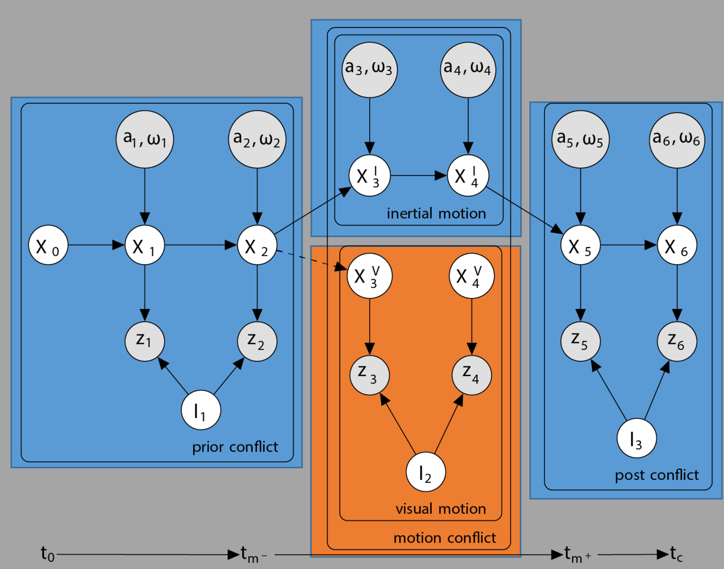
2 MOTION CONFLICT IN VIO

- Ego-motion is observable by both external (camera) and internal (IMU) sensors.
- When multiple motions are observed by sensors, determining which of these motions are consistent with ego-motion is essential.
- We term this as ***motion conflict.***

- Example of motion conflict - A moving camera in car sees static landmarks (green) and moving landmarks (red). Each group produce a different motion estimate.

3 MOTION CONFLICT MODEL

- A generalized Hidden Markov Model (HMM) for VIO in scenes with motion conflict.
- During motion conflict interval $[t_{m-}, t_{m+}]$ the state of the system is forked.
- We perform separate estimation of states X_k^V and X_k^I using X_{m-} as a priori



$$\mathbf{X}_k^V := \left[\mathbf{p}_V^{VS\top},\ \mathbf{q}_{VS}{}^\top,\ \mathbf{l}_0^{V\top},\ \ldots,\ \mathbf{l}_n^{V\top}\right]_k^\top \in \mathbb{R}^3 \times S^3 \times \mathbb{R}^{4n}$$

$$\mathbf{X}_k^I := \left[\mathbf{p}_W^{WS\top},\ \mathbf{q}_{WS}{}^\top,\ {}^S\mathbf{v}_{WS}{}^\top,\ \mathbf{b}_g^\top,\ \mathbf{b}_a^\top\right]_k^\top \in \mathbb{R}^3 \times S^3 \times \mathbb{R}^9$$

$$\hat{\mathbf{X}}_k^V = \underset{\mathbf{X}^V}{\operatorname{argmax}} \mathrm{P}(\mathbf{X}_{m-})\,\mathrm{P}(\mathbf{X}_{k-1}^V \mid \mathbf{X}_{m-})\,\mathrm{P}({\mathbf{X}^V}_k \mid \mathbf{X}_{k-1}^V, \mathbf{z}^{i,j,k})$$

$$\hat{\mathbf{X}}^I = \underset{\mathbf{X}_k^I}{\operatorname{argmax}} \mathrm{P}(\mathbf{X}_{m-})\,\mathrm{P}(\mathbf{X}_{k-1}^I \mid \mathbf{X}_{m-})\,\mathrm{P}({\mathbf{X}^I}_k \mid \mathbf{X}_{k-1}^I, \mathbf{u}_k)$$

4 DETECTING MOTION CONFLICT

- To determine which state corresponds to X_{m-} and when to apply motion conflict resolution, the motion conflict interval $[t_{m-}, t_{m+}]$ needs to be estimated.
- Based on the discrepancy of the estimated poses:

$$\delta_{MC} = \|\hat{\mathbf{p}}_k^V - \hat{\mathbf{p}}_k^I\|_\Sigma$$

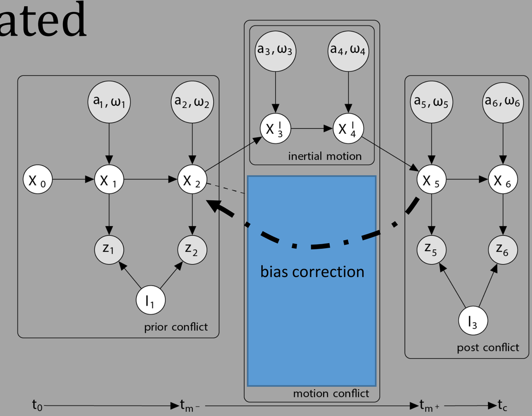
- Based on the landmarks l_j in the map, a per- landmark error δl_j is converted to per frame M_r.

$$\delta_{l_j} := \sum_{i \in S} (\mathbf{z}_{ij} - h(\mathbf{X}_i^I, \mathbf{l}_j)) \qquad M_r := \frac{\#\ \text{landmarks without conflict}}{\#\ \text{landmarks}}$$

5 RESOLVING MOTION CONFLICT

- After t_{m+}, X_I is propagated to estimate states in $[t_{m-}, t_{m+}]$.
- X_{m+} is the state estimate with visual measurements after t_{m+}.
- The states in interval $[t_{m-}, t_{m+}]$, are updated using back-propagation of state X_{m+}.
- IMU dominated motion conflict resolution (Mode 1):
  - The bias post motion conflict $\mathrm{b}_{a_{m+}}$ is interpolated backwards to estimate bias in interval $[t_{m-}, t_{m+}]$.

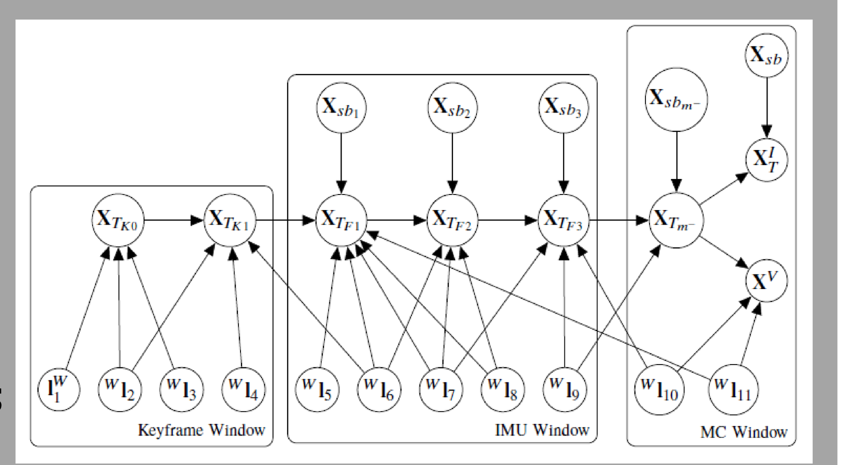
$$\mathbf{b}_a{}^I(t) = \frac{t - t_{m-}}{t_{m+} - t_{m-}}(\mathbf{b}_{a_{m+}} - \mathbf{b}_{a_{m-}}) + \mathbf{b}_{a_{m-}}$$



- Selective motion conflict resolution (Mode 2):
  - Visual measurements from landmarks that are consistent with the X_I are additionally to estimates states in interval $[t_{m-}, t_{m+}]$.

6 MC-VIO

- The detection and resolution techniques are combined to implement Motion Conflict aware Visual Inertial Odometry (MC-VIO)
- In keyframe window, marginalized states and the associated landmarks are maintained.

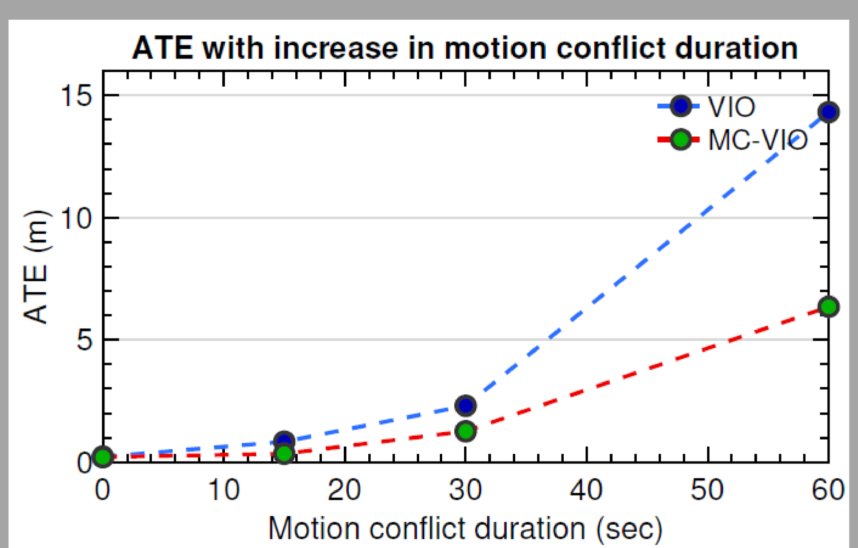


- In IMU window, consecutive frames without marginalization are maintained.
- MC window is only maintained when motion conflict is detected.

7 QUANTITATIVE RESULTS

Evaluation of MC-VIO on motion conflict simulated EuROC dataset

EuROC Dataset	ATE $[m]$			RPE $[m/s]$		
	VIO	Mode1	Mode2	VIO	Mode1	Mode2
mean	0.934	**0.349**	0.365	0.334	0.254	**0.244**
std.	0.778	0.179	0.178	0.218	0.152	0.157



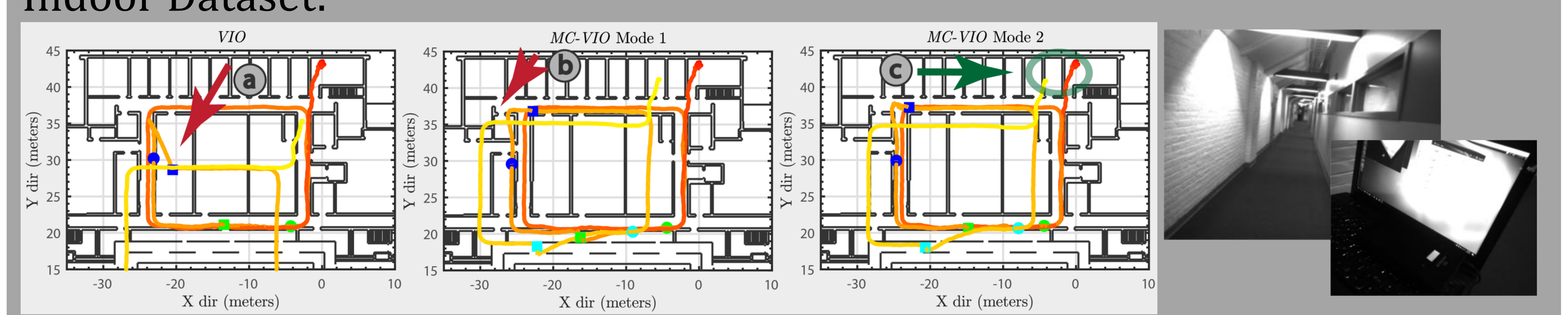
MC-VIO reduces increase in ATE by 80% and RPE by 60% for scenes with motion conflict, in comparison to the state-of-the-art reference VIO[1].

With MC-VIO, the ATE grew much slower than reference VIO algorithm[1] with increase in motion conflict duration.

[1] Stefan Leutenegger et al. Keyframe-based visual–inertial odometry using nonlinear optimization. The International Journal of Robotics Research, 2015.

8 QUALITATIVE RESULTS

Indoor Dataset:



Outdoor Dataset:

a Motion conflict creates large drift in reference VIO[1]

b MC-VIO – Mode 1produces resultant trajectory that had reduced drift

c MC-VIO – Mode 2 produces resultant trajectory that had least drift.

9 CONCLUSION

- In visually and inertially challenging environments, if **motion conflict** is not handled correctly, large irreversible errors occur in Visual Inertial Odometry.
- A generalized HMM can be used to model motion conflict. Novel approaches for detection and resolution were combined in our Motion Conflict aware Visual Inertial Odometry (MC-VIO) algorithm. Results indicated that MC-VIO **reduced the increase in ATE by 80% and RPE by 60%.**