On-Manifold Preintegration Theory for Fast and Accurate Visual-Inertial Navigation

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1 Method

- The method proposes a way to summarize multiple inertial measurements into one single constraint. The idea of preintegration has been proposed earlier in [1]. The downside of this earlier work being parameterization of attitude using euler angles. In addition there are number of interesting things proposed here.
- Typically when summarizing multiple measurements, they have dependence on the initial state estimate from which integration is carried out. The lopside of this being, the integration has to be repeated whenever the linearization point changes [2]. And this is computationally expensive.
- The preintegrated inertial measurements are parameterized such that they do not depend upon the initial conditions at the start of integration!
- The terms however depend upon bias. And this could change during iterative optimization. Two solutions can be proposed;
  - Recalculate the integrations again. This is expensive.
  - Instead given an update to the bias, update the original measurements using first order expansion. This is a very approach. Further experiments have shown that such a first order update is very close to the true value when integrations are recomputed. Figure 1 shows the difference (error) between actual re-integration and using first order updates.
- Additionally, all landmarks from the state are eliminated using conditional elimination. This reduces large number of variables from the optimization i.e, Structureless vision approach. It gets even better. The cost function for structureless vision residuals is further modified to get a more computationally feasible term.
- Most of the computation performed is derived in a very optimal way i.e, covariance of state for inertial residuals is propagated linearly instead of recomputing from scratch. Jacobians are linearly computed with each newly added measurement.
- Advantages gained over Euler-parameterizations:
  - Quite apparent is the singularity as pitch approaches 90° in an zyx rotation convention.
  - If one were to naively use Euler-parameterization in smoothing based frameworks by minimizing negative log-likelihood, this is not invariant under rigid body transformations. Serious consequence of this being, maximum-a-posterior estimate depends on the choice of the world frame of reference.
- The entire framework uses incremental smoothing as proposed in [3] keeping the computation time constant even while optimizing entire history of states.
- The method is shown to outperform both state-of-the-art in filtering based approaches and non-linear optimization based methods.

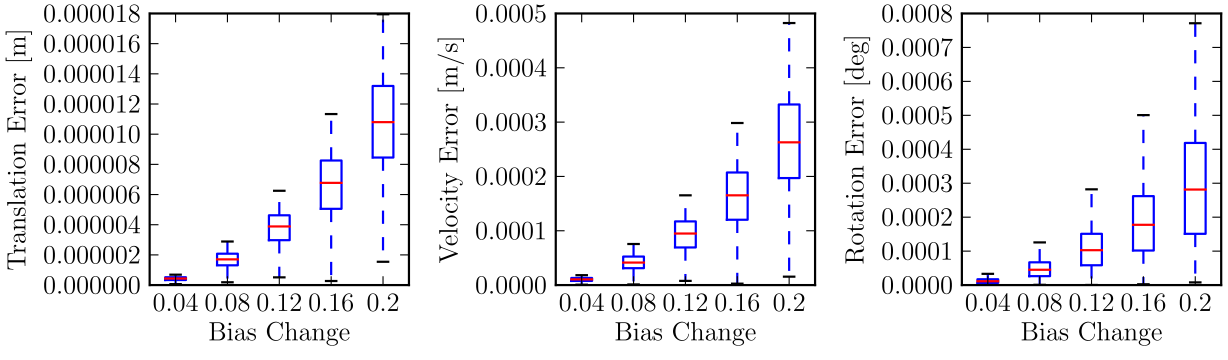

Fig. 1: Bias prediction error. Image taken from [4]

2 Related work summary

The reference numbers here are from [4].

Filtering

1. Complexity grows quadratically with #landmarks. ~20 are tracked
2. Structureless approach is elegant. landmarks are eliminated [5] but previous poses to be kep via stochastic cloning [13].
3. All measurements need to be ready before being used. Inefficient since we are not using all info.
4. Marginalization causes errors to be locked. And there could be potential outliers
5. Linearization errors cause drift and eventually render the system inconsistent => overconfident => estimates of covariance isn't correct => non-optimal fusion of different measurements.
6. Wrong linearization adds spurious information in the yaw direction => rendering only 3 unobservable directions. [1, 15, 19] gives detailed analysis on observability properties of VIN.

Fixed-lag smoothing

1. Older states get marginalized out Hence, certain properties of Filtering approaches are shared here as well. (accumulation of linearization errors, inconsistency because of marginalization) [18, 22, 26]
2. These are robust to outliers to a certain extent since these can be rejected after optimization.
3. [20 - 24]

Full smoothing

1. Entire history is optimized but becomes computationally infeasible.
2. Only subset of certain frames are kept (keyframes) and the the rest are discarded. [24, 32-34]
3. Typically the optimization is run in a parallel thread. [20, 35]
4. iSAM2 is incremental approach relying on factor-graphs where only those states are updated which are affected by a new measurement.

Use of IMU at high rates

1. Typically it requires that you add states at 1KHz. Just not possible computationally
2. Generate relative motion constraints by integration b/w two keyframes. [24, 30, 38-40]
3. Typically this constraint depends on state at the start of integration requiring to recalculate the integration when the linearization point changes (at every iteration of optimization). [24]
4. Euler angles used in [2] is not invariant under the action of rigid body transformations [41, 42]

Fig. 2: VIN approaches

3 Detailed references to be followed up with

Detailed reference section for further in depth reading of material. The reference numbers here are from [4].

- 2: Introduces preintegration theory.
- 4, 5: Introduces structureless vision model. In [5], this model is used but the way this is used in the current paper, there are two main advantages:
  1. Addition of measurements need not be delayed
  2. The measurements can be relinearized multiple times.

References

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