

Invariant filtering framework for multibody pose estimation

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1 Introduction

Pose estimation is an active research topic in robotics. For instance, in human-robot interactions, accurately estimating the operator’s pose is essential for the robot to ensure safety and prevent potential harm. Vision-based pose estimation techniques are undoubtedly the most popular due to their exceptional performance, but they rely on maintaining a clear line of sight with the target, which is not always feasible. In such cases, Inertial Measurement Units (IMUs) mounted on the target system offer a compelling alternative by enabling greater freedom of motion. The impact of IMU drift on pose estimation quality is then mitigated using robust filtering methods.

The Extended Kalman Filter (EKF) is the standard filter for many nonlinear filtering applications. Nevertheless, it does not account for the geometry or symmetries inherent to many systems. This limitation inspired the development of the Invariant Extended Kalman Filter (IEKF), a geometrically grounded filtering method defined on matrix Lie groups [1]. The IEKF offers enhanced convergence properties for systems that are group-affine or involve observations expressed in invariant form—a common characteristic in attitude and pose estimation tasks [2, 3]. In this work, we extend the invariant filtering framework to estimate the extended pose (orientation, velocity, and position) of multibody systems—comprising multiple rigid bodies connected by kinematic constraints—using only IMUs.

2 Invariant filtering framework for pose estimation in multibody systems

Consider a multibody system with J rigidly connected bodies, as illustrated in Figure 1. Each body is equipped with an IMU and a corresponding frame F_{s_j} , while F_I represents the inertial frame. For simplicity and without loss of generality, we assume that the IMU and body frames are aligned, so that the extended pose of body j is given by

$$\chi_j = \begin{bmatrix} \mathbf{R}_j & \mathbf{v}_j & \mathbf{p}_j \\ \mathbf{0}_{1 \times 3} & 1 & 0 \\ \mathbf{0}_{1 \times 3} & 0 & 1 \end{bmatrix}, \quad (1)$$

with \mathbf{R}_j the rotation matrix from frame F_{s_j} to frame F_I , and \mathbf{v}_j and \mathbf{p}_j the velocity and position vectors of IMU j in F_I .

We advocate that the extended pose of the multibody system

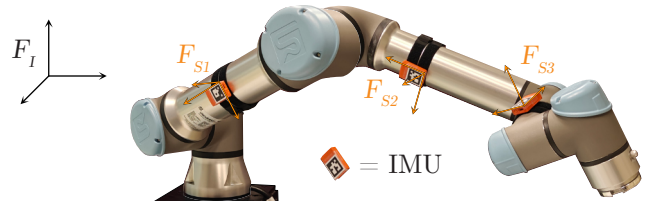


Figure 1: Multibody system ($J = 3$) equipped with IMUs.

can be represented by the state

$$\chi = \text{diag}(\chi_1, \chi_1^{-1} \chi_2, \chi_2^{-1} \chi_3).$$

This representation allows the kinematic constraints to be expressed in the invariant form $\chi \mathbf{d} = \mathbf{y}$, where $\mathbf{d}, \mathbf{y} \in \mathbb{R}^{5J}$ are known. These constraints can thus be treated as noise-free pseudo-measurements within the invariant framework.

Encoding noise-free information can introduce instabilities in the computation of the Kalman gain. To address this, we develop the Iterated IEKF. This iterative algorithm ensures that the probability distribution of the estimated state remains entirely within the constrained state space, excluding all states that violate the considered constraints.

3 Application

We benchmark the proposed framework against the EKF and Iterated EKF on a real-world extended pose estimation task, using three Xsens Awinda IMUs mounted on a UR5e robot. This setup is shown in Figure 1.

References

- [1] A. Barrau and S. Bonnabel, “The invariant extended kalman filter as a stable observer,” *IEEE Transactions on Automatic Control*, vol. 62, no. 4, pp. 1797–1812, 2016.
- [2] —, “The geometry of navigation problems,” *IEEE Transactions on Automatic Control*, vol. 68, no. 2, pp. 689–704, 2022.
- [3] R. Hartley, M. Ghaffari, R. M. Eustice, and J. W. Grizzle, “Contact-aided invariant extended kalman filtering for robot state estimation,” *The International Journal of Robotics Research*, vol. 39, no. 4, pp. 402–430, 2020.

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