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RNN-based state and parameter estimation for sparse magnetometer-free inertial motion tracking

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Abstract: Inertial measurement units are widely used for inertial motion tracking (IMT) in numerous applications. Although both magnetometer-free IMT and sparse IMT have distinctive advantages, their combination has rarely been achieved. Recently, recurrent neural network-based observers (RNNOs) have been successfully used for IMT but under the assumption of precisely known chain geometries (segment length, sensor-to-segment positions). However, in practice the geometry is generally unknown. We propose RNNOs that estimate the relative pose of three-segment kinematic chains with double hinge joints despite unknown chain geometries and which can be used to enable magnetometer-free, sparse, and self-calibrating IMT.

I. Introduction

Inertial measurements units (IMUs) are nowadays widely applied in a broad range of application domains [1]. These applications often involve tracking the motion of a concretization of a kinematic chain using magnetometer-aided (9D) IMUs and one IMU per segment. However, 9D IMT should be avoided as distortions in magnetic fields can degrade the accuracy of orientation estimates [2]. Additionally, omitting individual IMUs—referred to as sparse sensor setups—would lead to reduced effort and cost. Although magnetometer-free and sparse IMT has distinctive application advantages, it has rarely been achieved so far [3]; mainly, as it is prone to lead to non-observable systems, in which multiple motions may generate the same measurements.

Recently, recurrent neural networks (RNNs) have been successfully used to analyze the observability properties of double hinge-joint systems [4]. There, an RNN-based observer (RNNO) is able to estimate the relative orientations of a three-segment kinematic chain with double hinge joints and only a sparse set of two 6D IMUs in simulation. It was assumed that the geometry of the kinematic chain (lengths of segments, sensor-to-segment positions) is known. This is a major restriction, as in practice, the geometry may well be unknown and calibration is time-consuming and error-prone.

Here, we investigate whether RNNO can estimate the relative pose of a three-segment kinematic chain with double hinge joints across a wide range of chain geometries from only sparse sensors, without magnetometer readings, and without any prior knowledge of the chain geometry at hand.

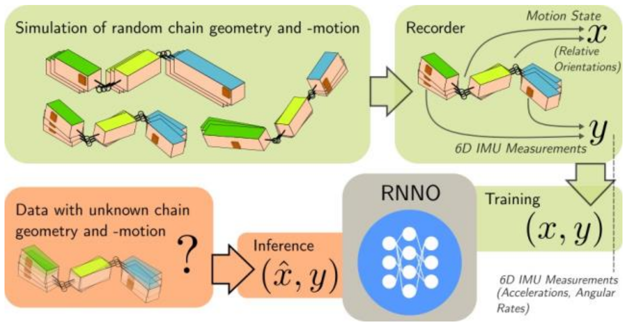

Figure 1: The RNN-based observer (RNNO) is trained on automatically generated data of random chain motion performed by a chain with random geometry. It learns to estimate relative orientations of a three-segment kinematic chain connected by double hinge joints from measurements of two 6D IMUs. After training, RNNO can estimate an unknown chain motion performed by a wide range of unknown chain geometries.

II. Problem Formulation

We consider a kinematic chain consisting of three segments with frames $\mathcal{S}_1, \mathcal{S}_2, \mathcal{S}_3$ connected by double (two) hinge joints with known and non-parallel joint axes directions. The complete geometry of the chain, including the segment lengths and sensor-to-segment positions, is unknown. Only the two outer segments are equipped with 6D IMUs and their measurements are combined into one signal $y(t) \in \mathbb{R}^{12}$ defined as $y(t) = (\omega_1(t)^\intercal, \rho_1(t)^\intercal, \omega_3(t)^\intercal, \rho_3(t)^\intercal)^\intercal$ where $\omega_i(t), \rho_i(t)$ denote gyroscope and accelerometer measurements of the first and second IMU. Subscripts are used to refer to segment frames. We assume that sensor-to-segment orientations are known. The relative pose of the kinematic chain is fully determined by the state $x(t) \in H^2$ with $x(t) = \left({}^{\mathcal{S}_1(t)}_{\mathcal{S}_2(t)}q^\intercal, {}^{\mathcal{S}_3(t)}_{\mathcal{S}_2(t)}q^\intercal\right)^\intercal$ where ${}^{\mathcal{S}_1(t)}_{\mathcal{S}_2(t)}q \in H$ denotes the unit quaternion that represents the orientation between segment one and two. We assume that initial relative orientations are known. The goal is then to estimate the current relative pose $x(t)$ from the current and previous measurements $y(1{:}t)$.

III. Proposed Method

Our method consists of an RNNO which is trained on an endless stream of data generated just-in-time using the random chain motion generator (RCMG) as proposed in [4]. RNNO learns to estimate the relative pose of the kinematic chain from IMU measurements that include realistic simulated noise and bias levels. The RCMG can be viewed as function that given a random seed computes the sequences $x(1{:}T)$ and $y(1{:}T)$ with a sequence length of $T = 60$ seconds. Further details on the internals of the RCMG and the network architecture of RNNO can be found in [4]. In addition to that, we extend the RCMG to simulate chain motion performed by a chain with a randomly drawn geometry. The chain geometry is defined by nine parameters, two 3D vectors defining the sensor-to-segment positions and three segment lengths. Here, we extend RCMG with functionality enabled through a flag `randGeo`. If set, RCMG (internally) draws each of the nine parameters that define the chain geometry of the chain to be simulated i.i.d. from $\sim \mathcal{U}(-0.5{,}0.5)$m. The signature of the RCMG is `RCMG(seed: integer, randGeo: boolean)`.

IV. Results and Discussion

We show that the proposed extension to the RCMG enable RNNO to generalize across chain geometries and estimate the relative pose of chain motion performed by a wide range of chain geometries. Fig. 2 shows the estimation performance of the trained RNNO on one example sequence. RNNO has no prior knowledge of the chain geometry that generated the sequence, still, the predicted joint angles always track the true joint angles closely. Fig. 3 shows the effect of the `randGeo` flag on the trained RNNO. If set, RNNO can achieve a low root-mean-squared (angle) error (RMSE) when evaluated on a wide range of chain geometries.

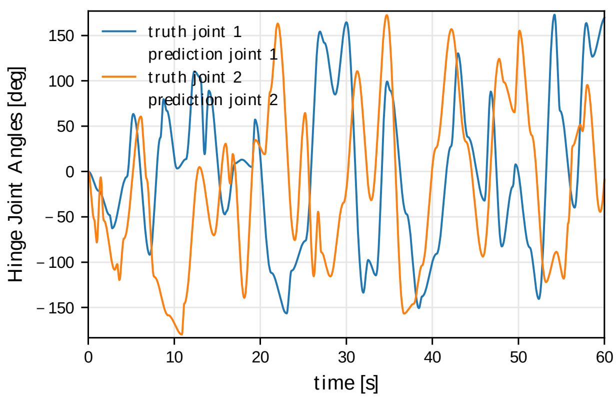

Figure 2: Trained RNNO's performance on one example sequence. RNNO can track both hinge joint angles of a three-segment kinematic chain using measurements from a sparse set of IMUs without knowledge of the chain's geometry.

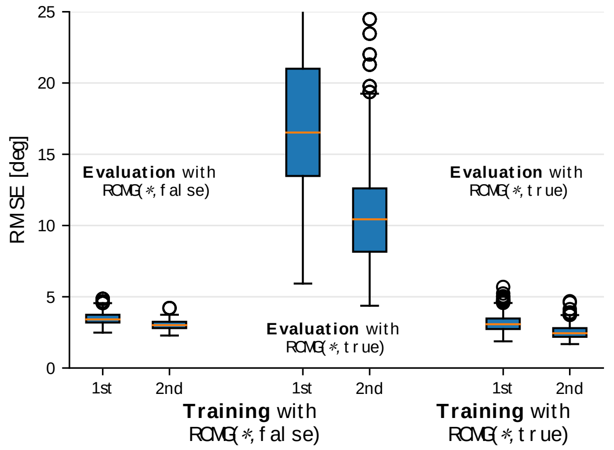

Figure 3: Trained RNNO's performance of the first and second hinge joint angle. For the four leftmost boxplots RNNO has been trained for 1500 episodes containing each 2048 sequences sampled from an endless stream of sequences of random chain motion but performed by a chain with one fixed geometry, i.e. the flag of the RCMG, that randomizes chain geometry, is unset. Whereas on the two rightmost boxplots RNNO has been trained equally long but on sequences where for each sequence the chain geometry is drawn randomly. To evaluate the trained RNNO 2048 (new) sequences are generated using the RCMG with the flag either set or unset. The Asterisk denotes one of many seeds. The proposed extension enables RNNO to generalize across a wide range of chain geometries.

V. Conclusions

We have used RNNOs to enable magnetometer-free, sparse, and self-calibrating inertial motion tracking. To the best our knowledge this is the first method which combines these key properties and their advantages, and it marks an important step towards making inertial motion tracking more cost-efficient, effortless, and usable for a broad range of existing and unexplored applications.

Future research aims to achieve a thorough experimental validation and to extend RNNO to joint setups that include higher degree of freedom joints and to generalize across joint axes and sensor-to-segment orientations.

References

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