Penn Engineering
UNIVERSITY of PENNSYLVANIA

ICLR

EqNIO: Subequivariant Neural Inertial Odometry


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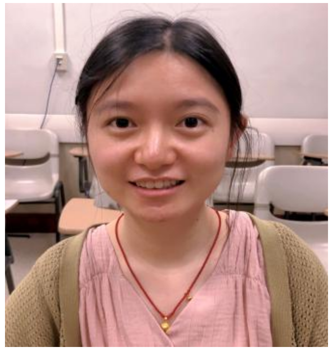
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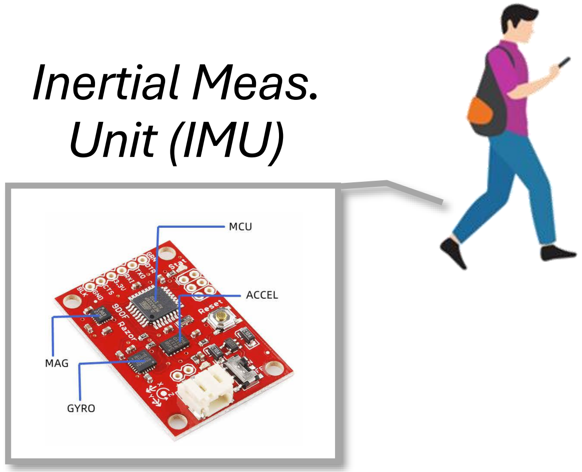
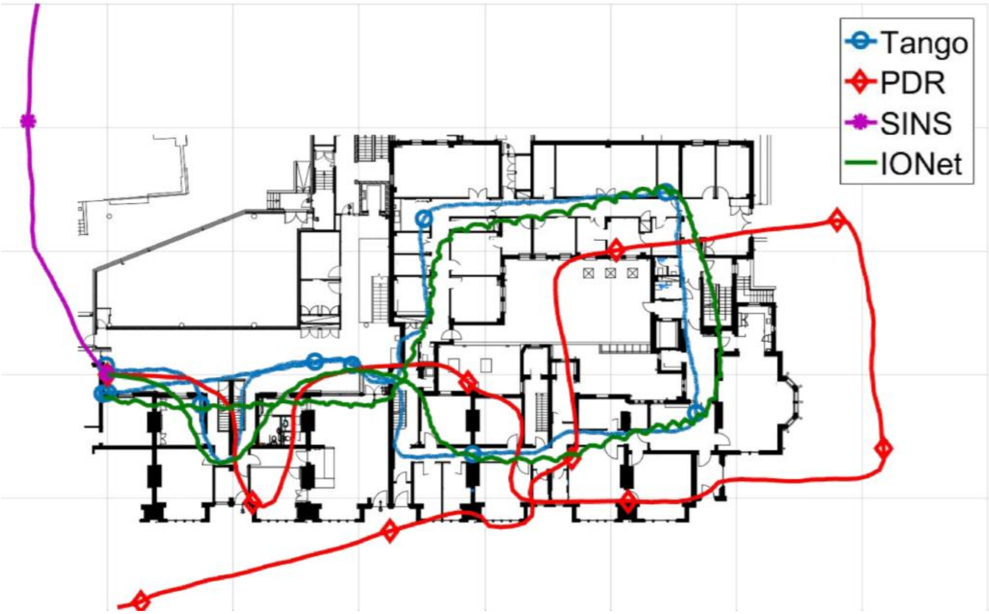
* denotes equal contribution, † denotes equal advising

Inertial Odometry (IO)

- **Goal:** Odometry from raw accelerometer and gyroscope measurements from an IMU.

Inertial Meas. Unit (IMU)





What does an IMU measure?

- Raw IMU measurements are related to true linear accelerations and angular velocities as follows:

$$\tilde{\omega}_i = \bar{\omega}_i + {b^g}_i + {\eta^g}_i$$

Raw IMU meas.

True meas.

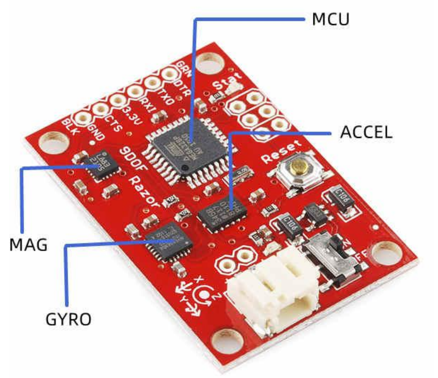
IMU Biases

Noises

$$\tilde{a}_i = \bar{a}_i - \boxed{{}^w_bR_i^T}\, g + {b^a}_i + {\eta^a}_i$$

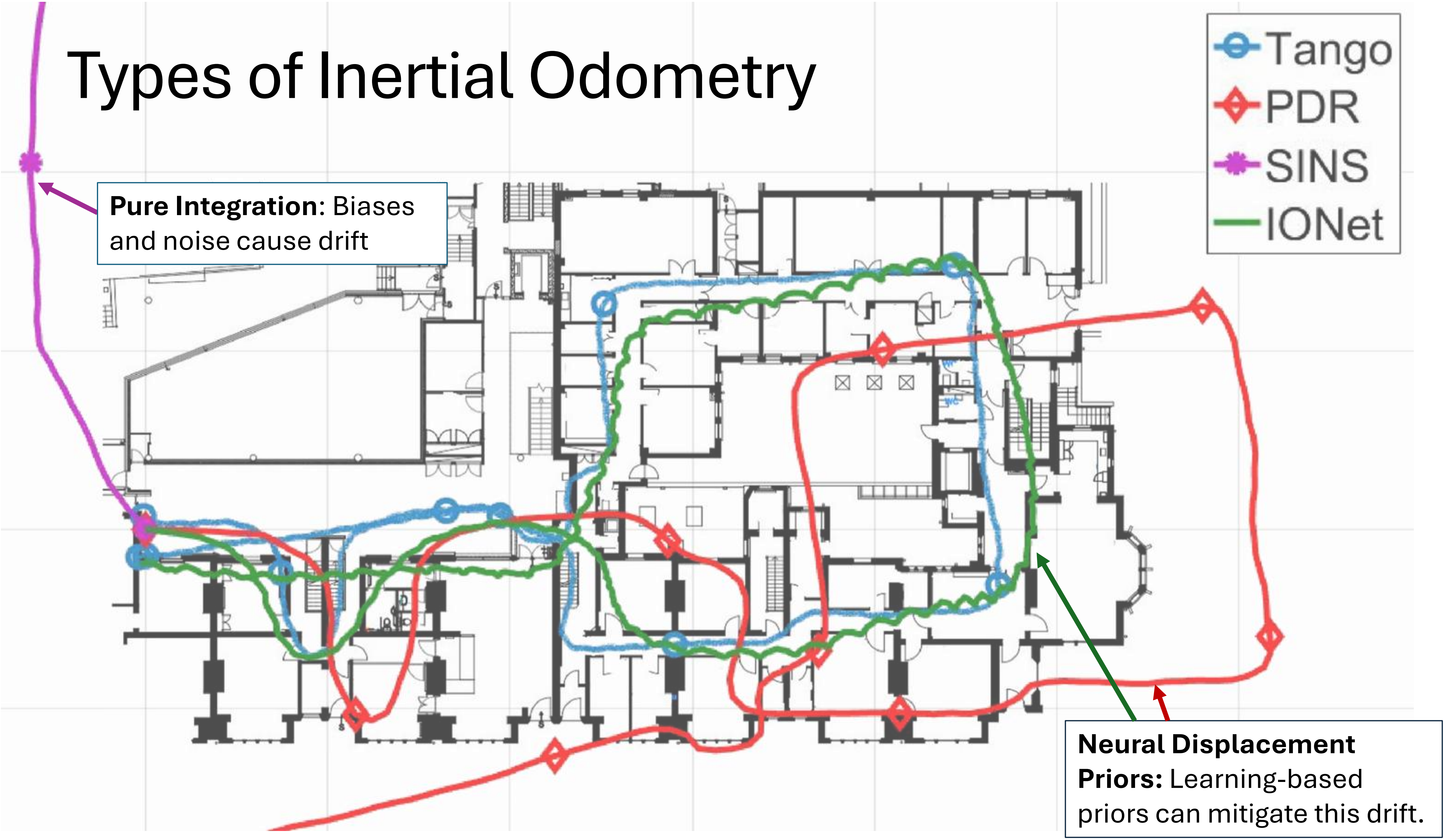
Transformation from body frame b to world frame w

Gravity vector pointing downwards in world frame

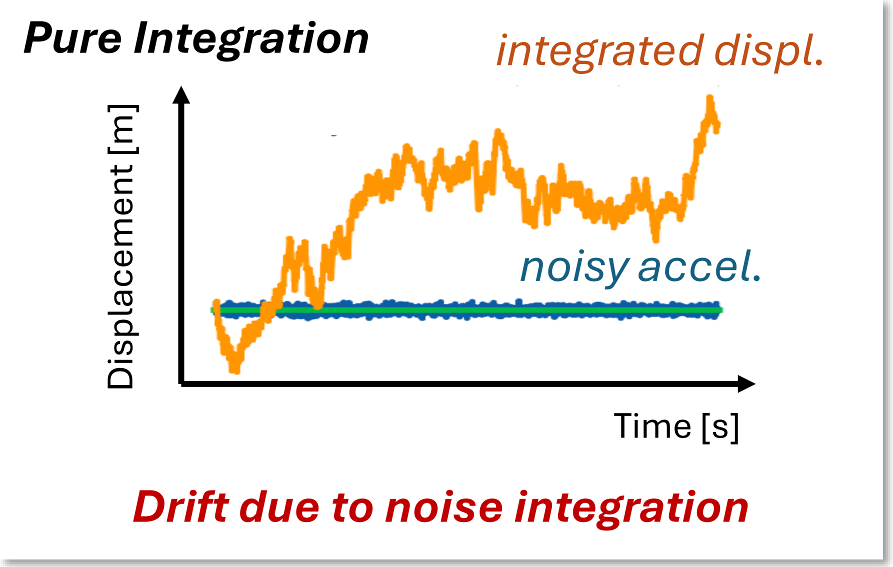


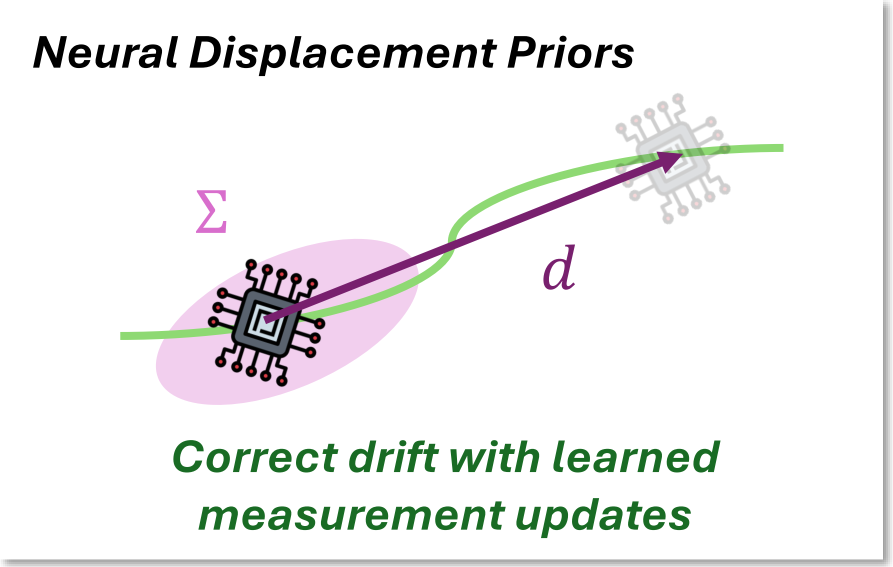
Inertial Meas. Unit (IMU)

Types of Inertial Odometry



Types of Inertial Odometry





What is a Neural Displacement Prior?

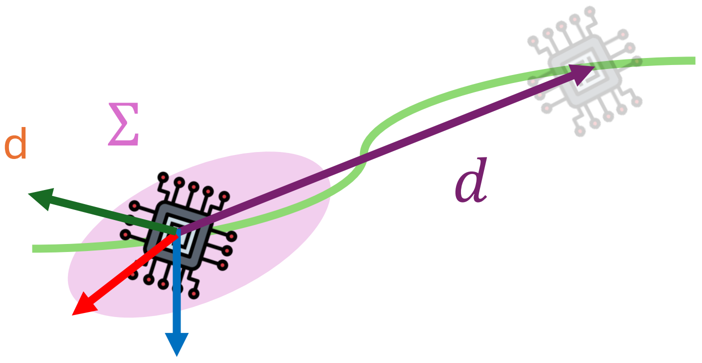
- From set of measurements

$$\omega_i = {}^g_bR_i(\tilde{\omega}_i - b^g)$$

Orientation wrt gravity aligned frame

Factory calibration biases

$$a_i = {}^g_bR_i(\tilde{a}_i - b^a)$$

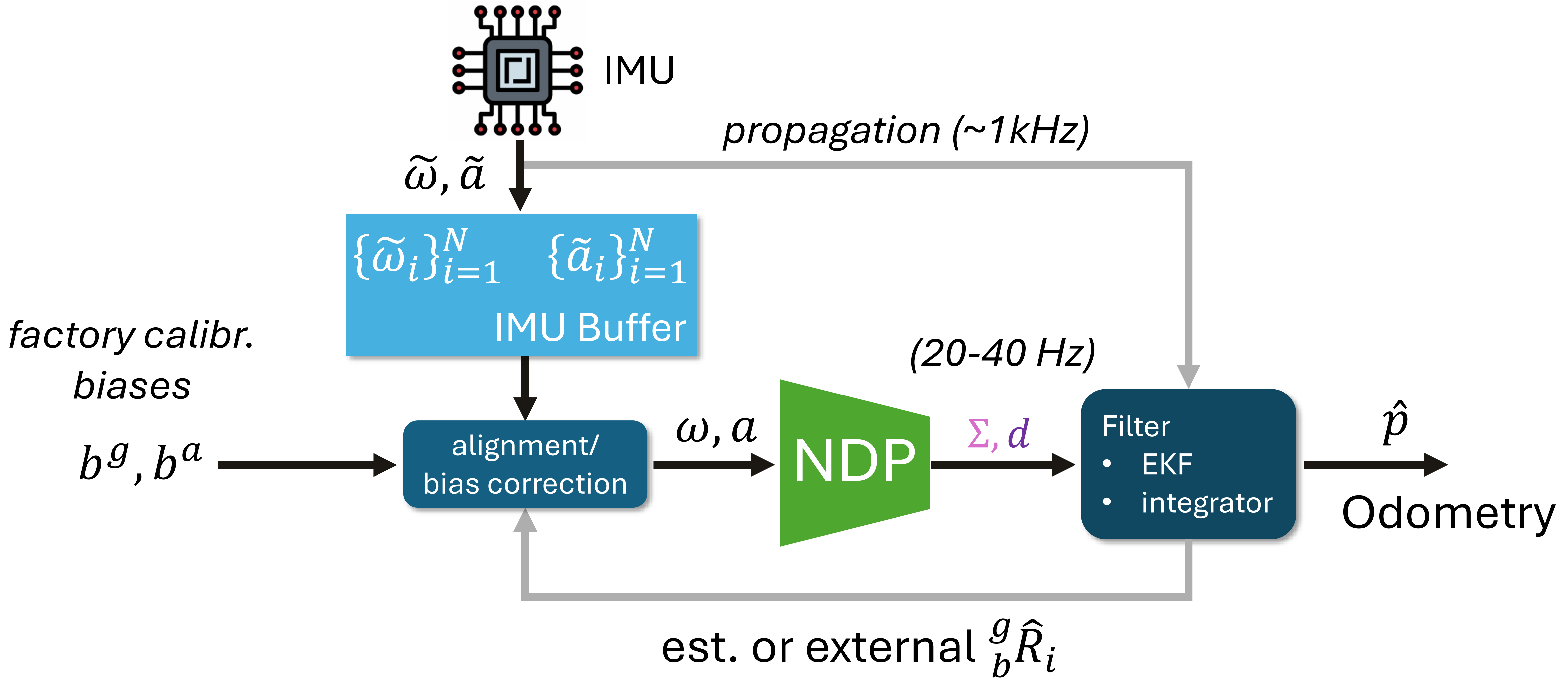


- Learn to regress displacement d and covariance Σ with neural network:

$$d, \Sigma = \Phi\left(\{\omega_i\}_{i=1}^N, \{a_i\}_{i=1}^N\right)$$

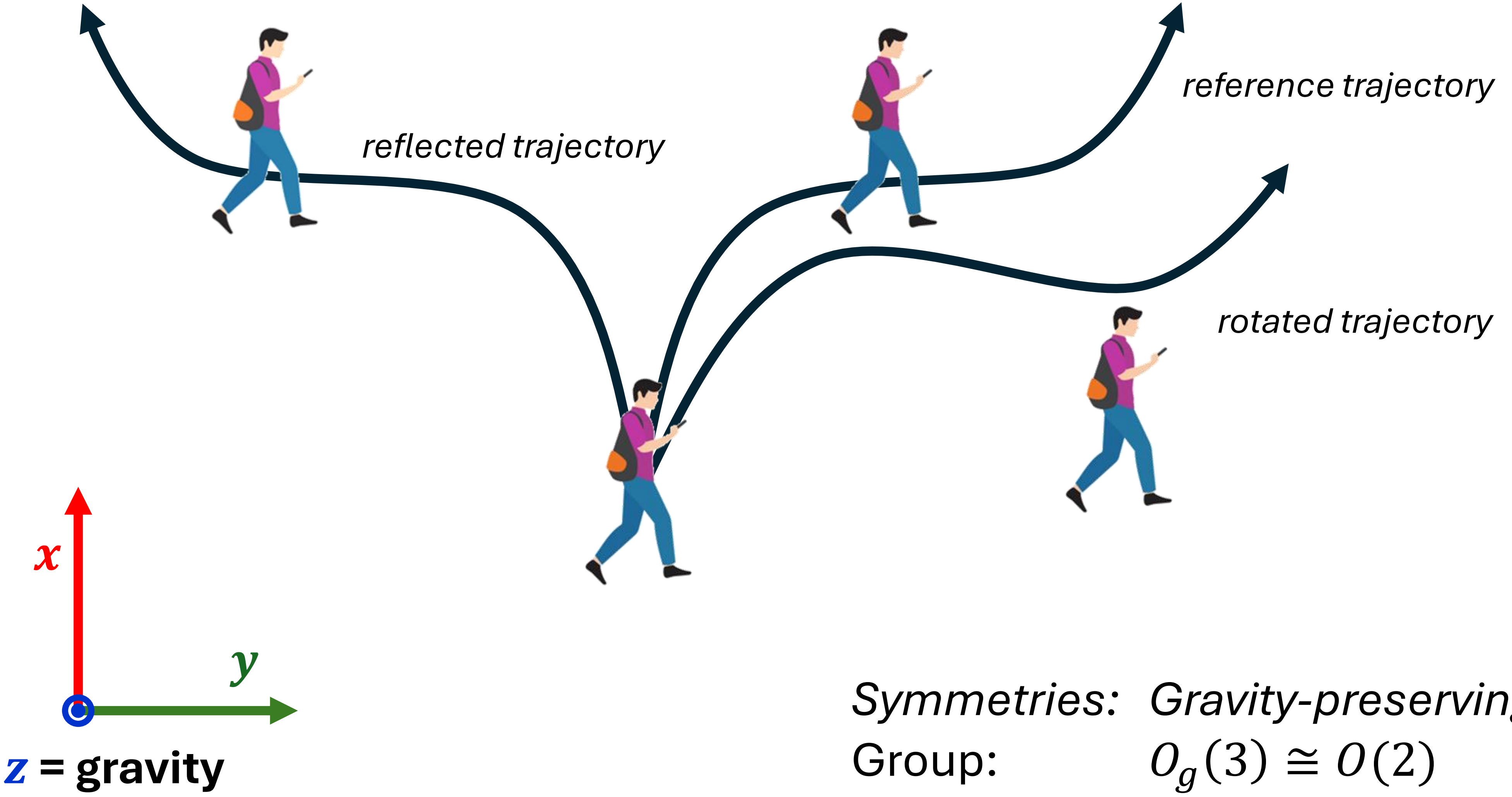
Neural Displacement Prior (NDP)

Neural Inertial Odometry



Herath et al., “RoNIN: Robust Neural Inertial Navigation in the Wild”, ICRA, 2020
Liu et al., “TLIO: Tight Learned Inertial Odometry”, R-AL, 2020

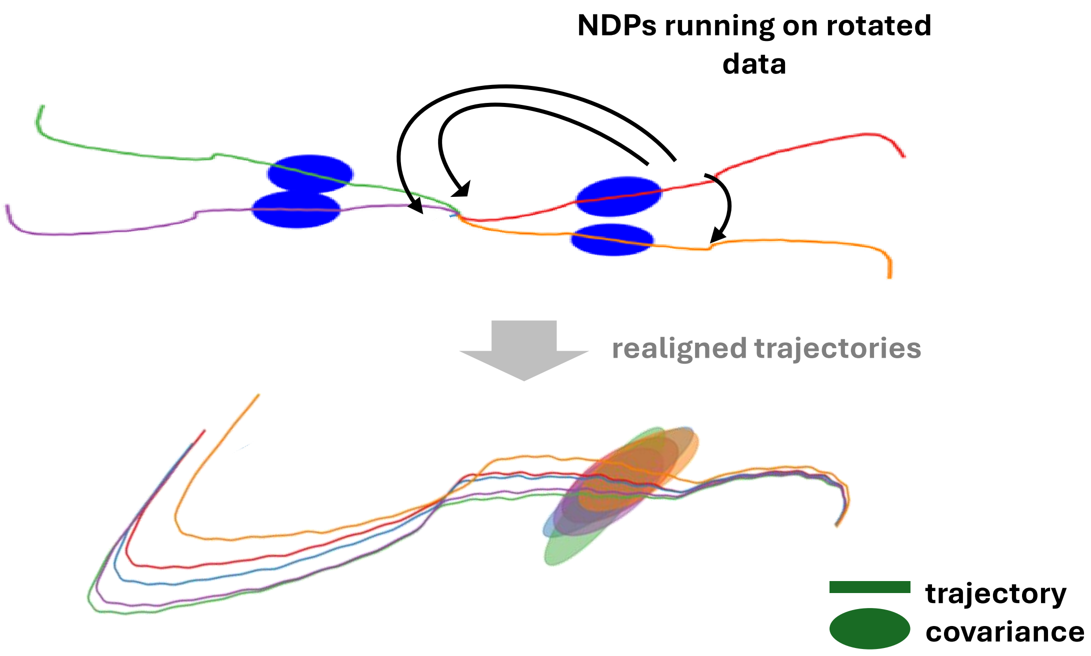
Symmetry in Neural Inertial Odometry



Symmetries: *Gravity-preserving roto-reflections*
Group: $O_g(3) \cong O(2)$

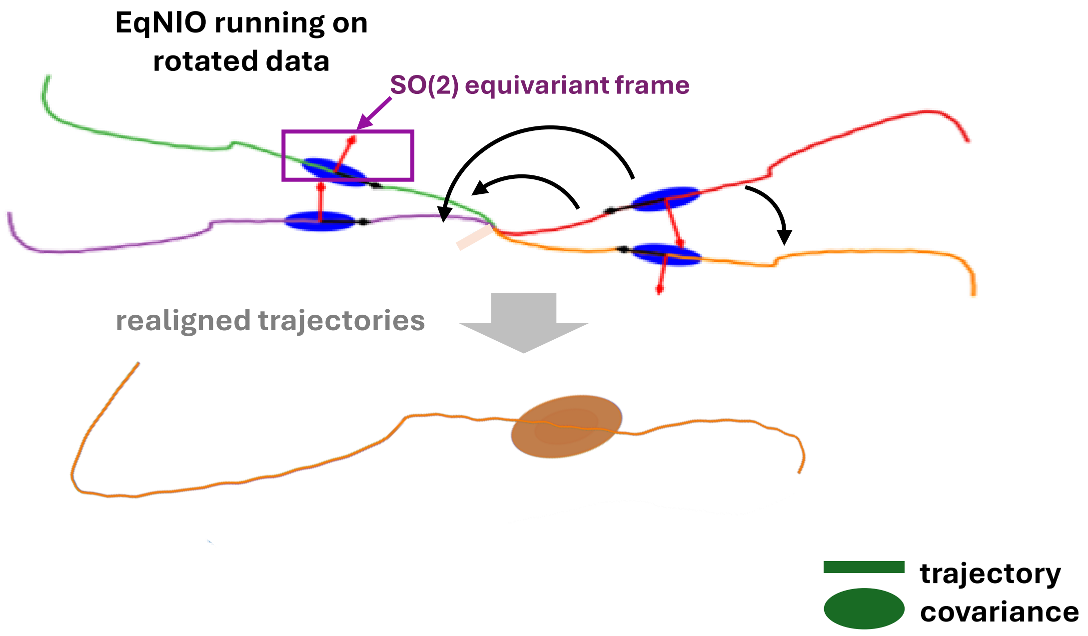
Symmetry in Neural Inertial Odometry

Prior Work (RoNIN, TLIO…)



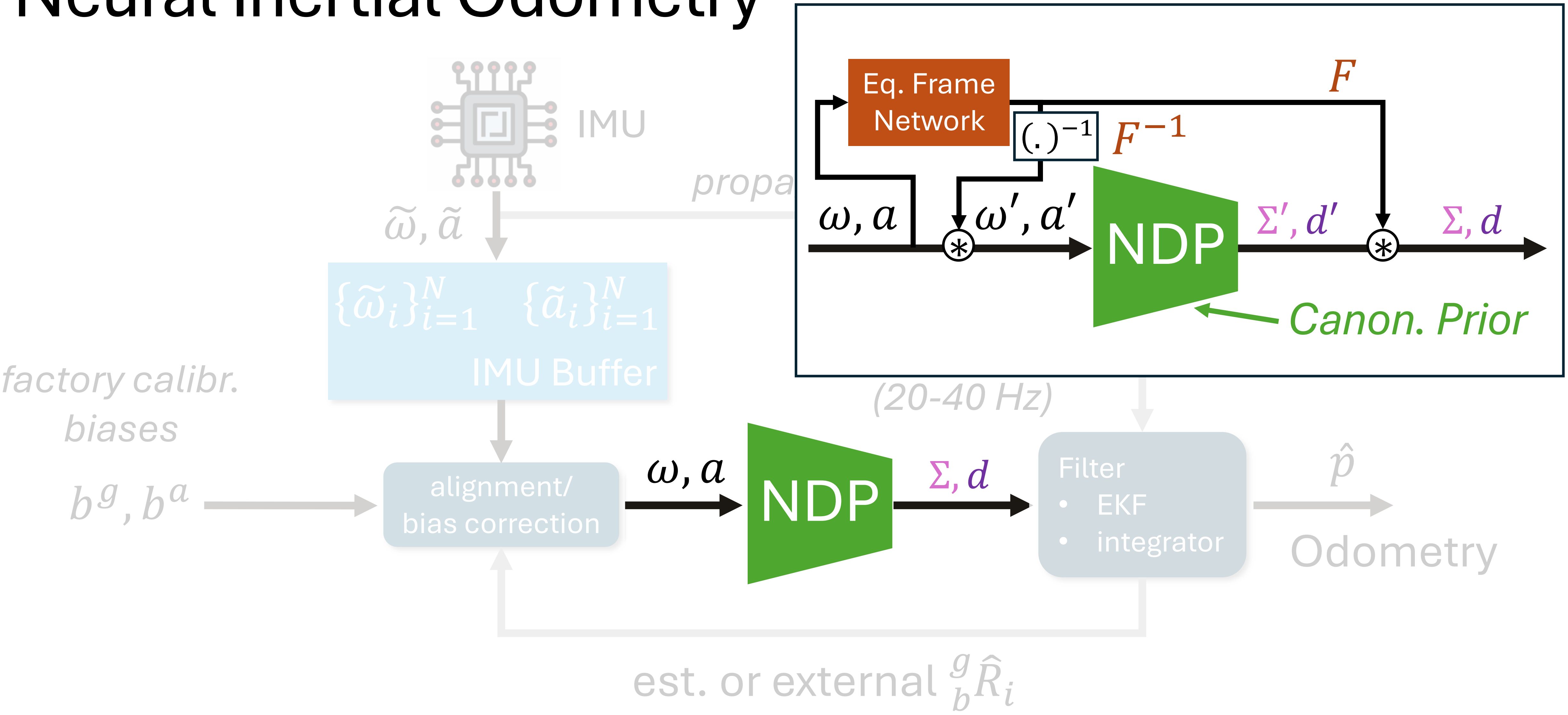
Inconsistent trajectories, despite data augmentation

EqNIO (this work)



Consistent trajectories thanks to equivariant processing

Neural Inertial Odometry



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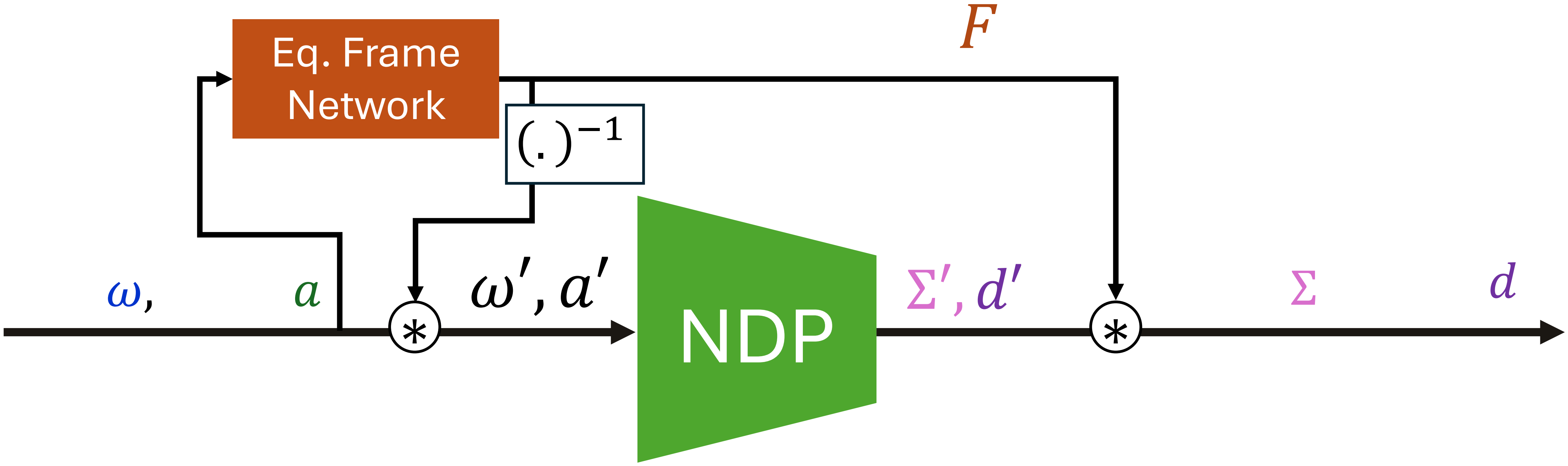
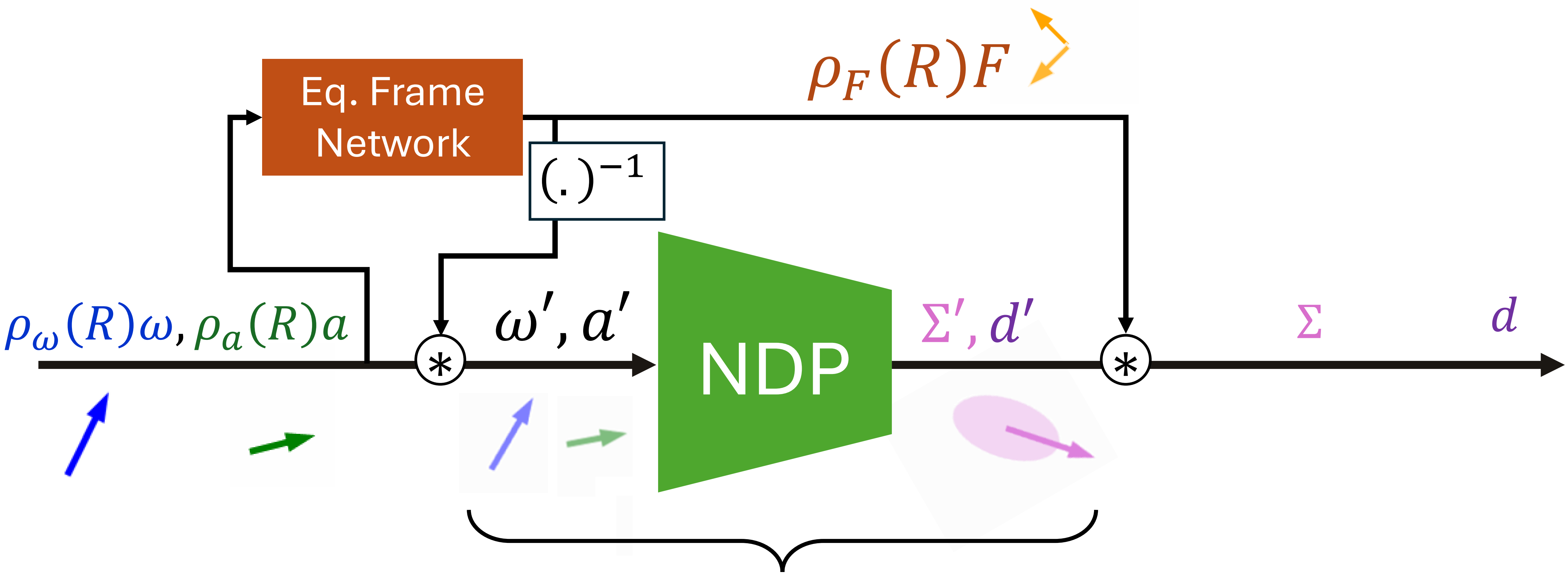
Equivariance of EqNIO



Equivariance of EqNIO

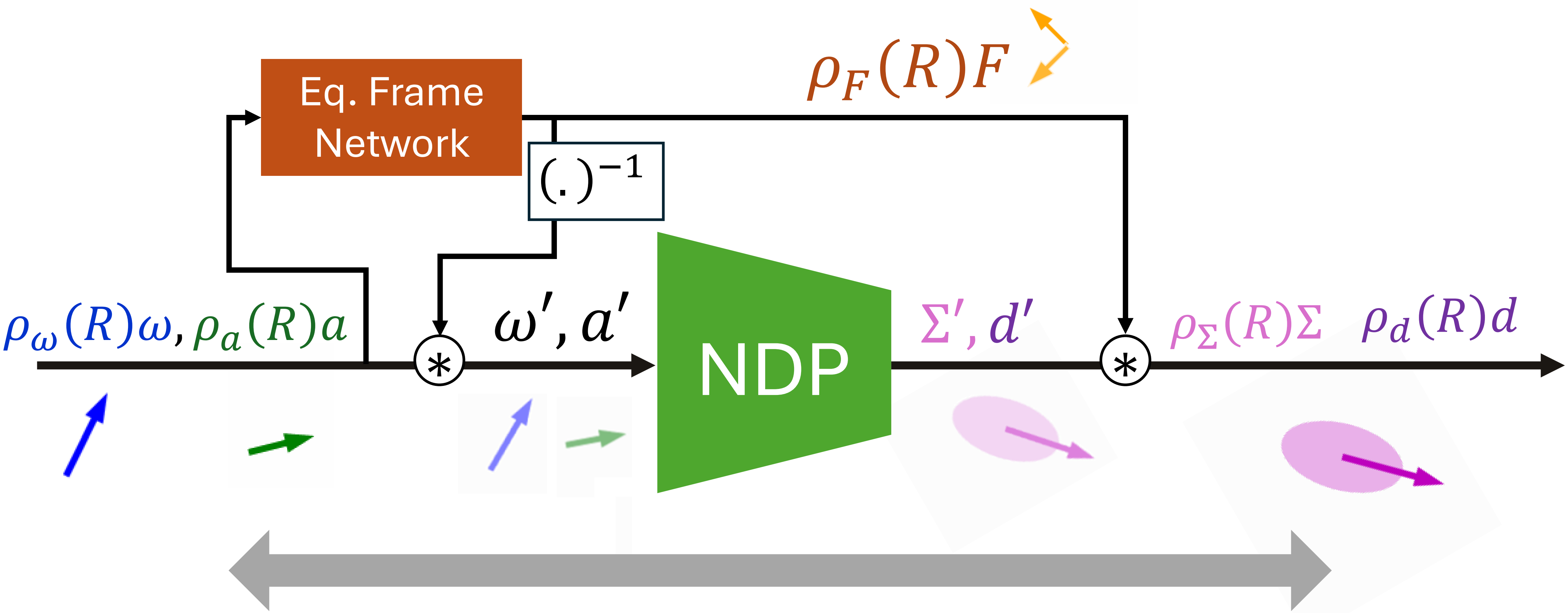
Yaw Symmetry $SO(2)$



simpler training in canonical space

Equivariance of EqNIO

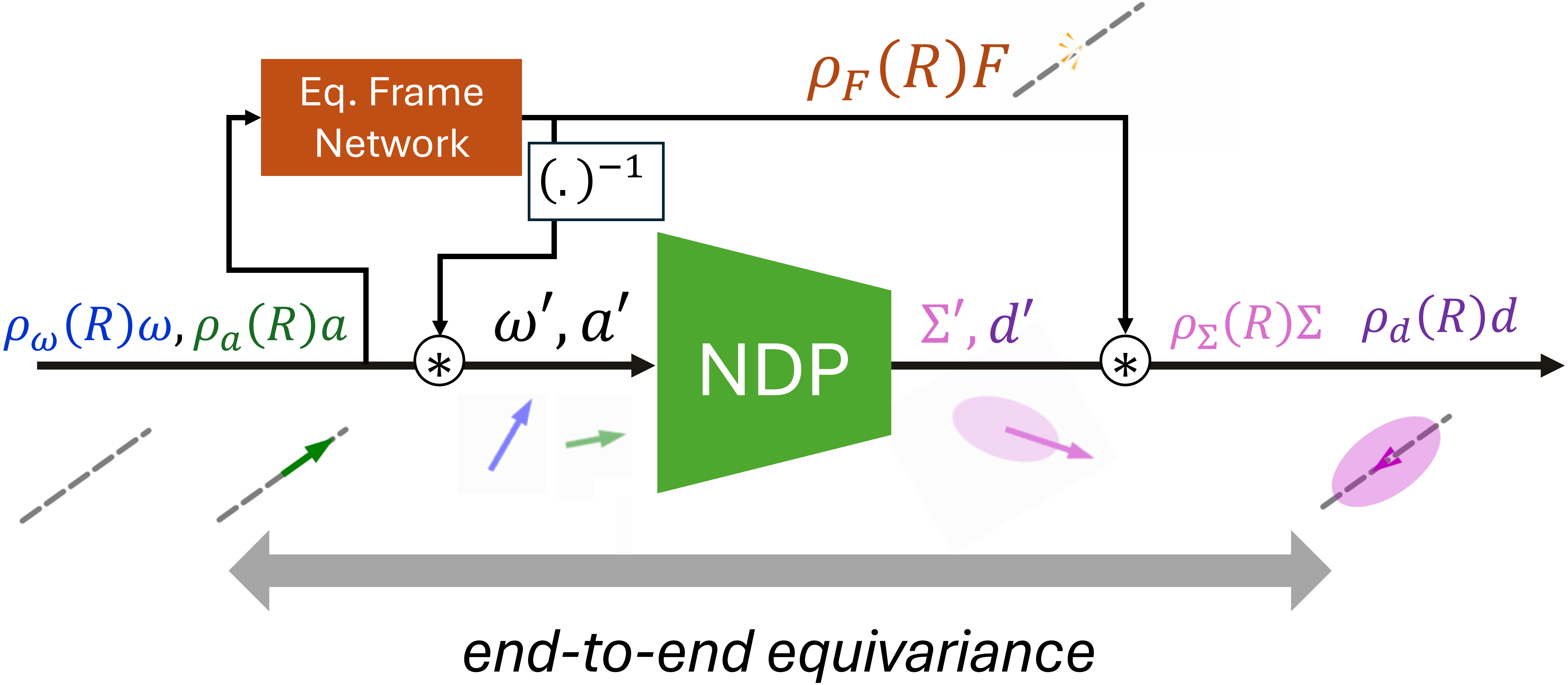
Yaw Symmetry $SO(2)$



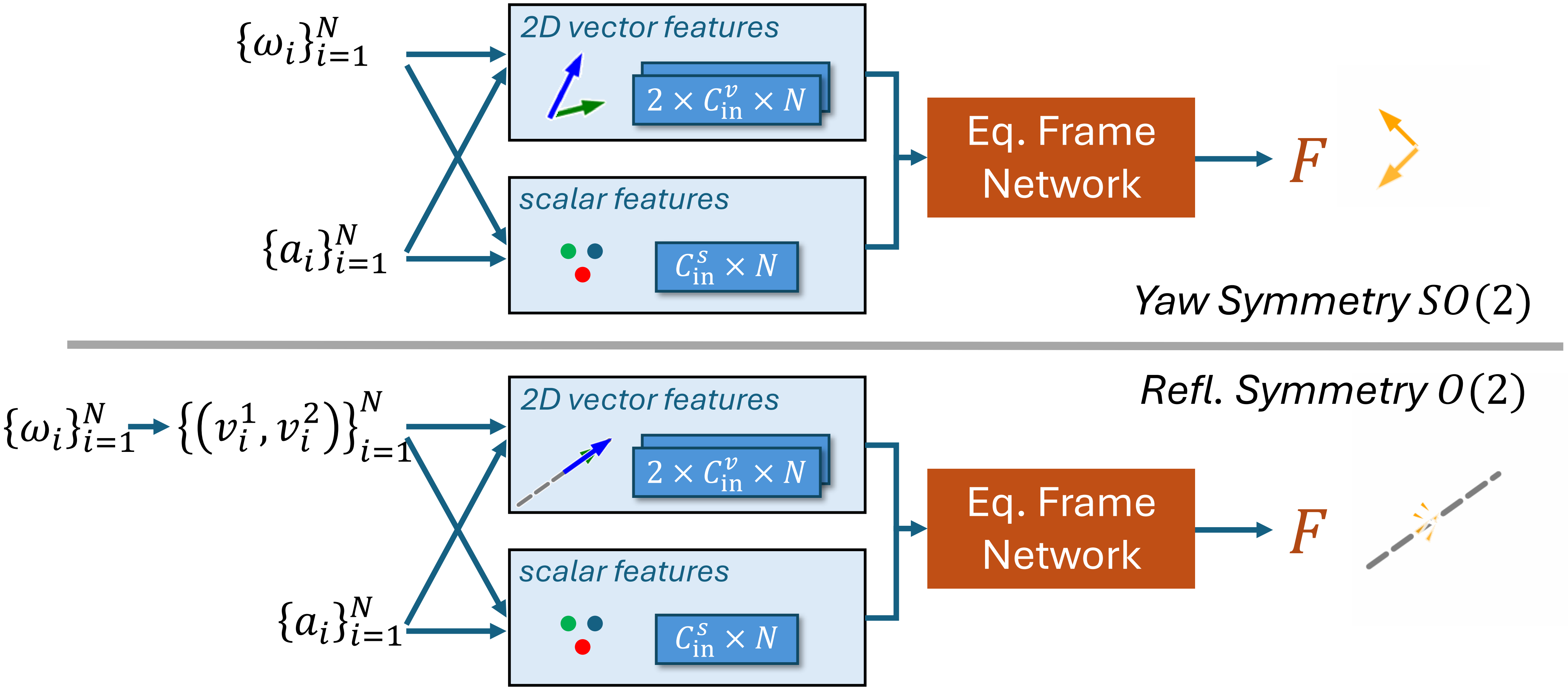
end-to-end equivariance

Equivariance of EqNIO

Reflection Symmetry $O(2)$



Building the Equivariant Frame

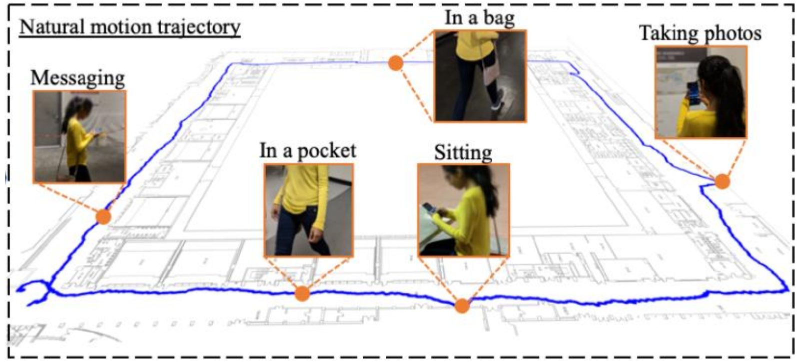


Experiments

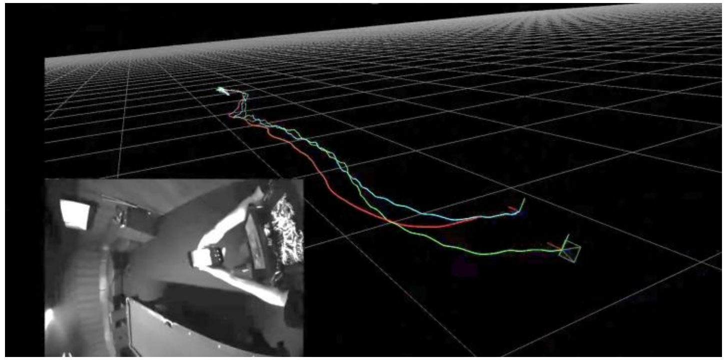
Extensive evaluation on **two NDPs (RoNIN, *TLIO*), *and 5 datasets***

*Consistent reduction of **absolute and rel. trajectory error (ATE/RTE)***

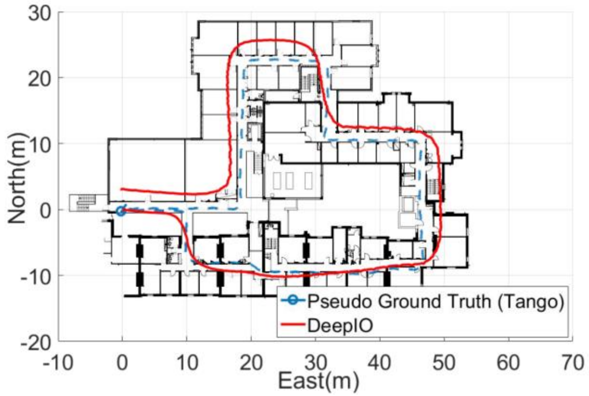
RoNIN Dataset



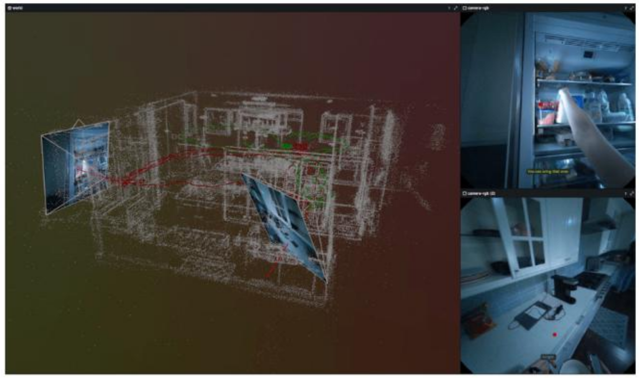
TLIO Dataset



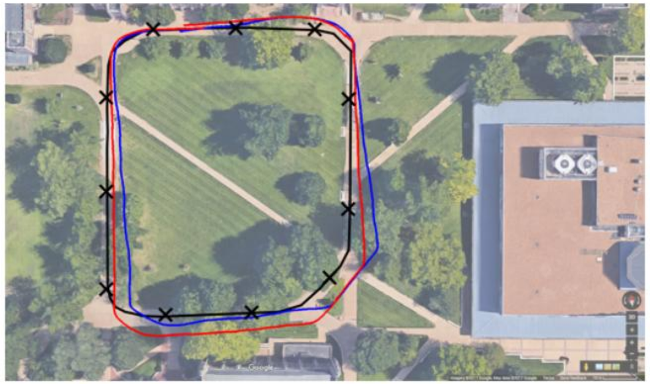
OXIOD Dataset



Aria Everyday Activities Dataset



RIDI Dataset



Application to RONIN

- Adding our **EqNIO** to RoNIN consistently improves results!

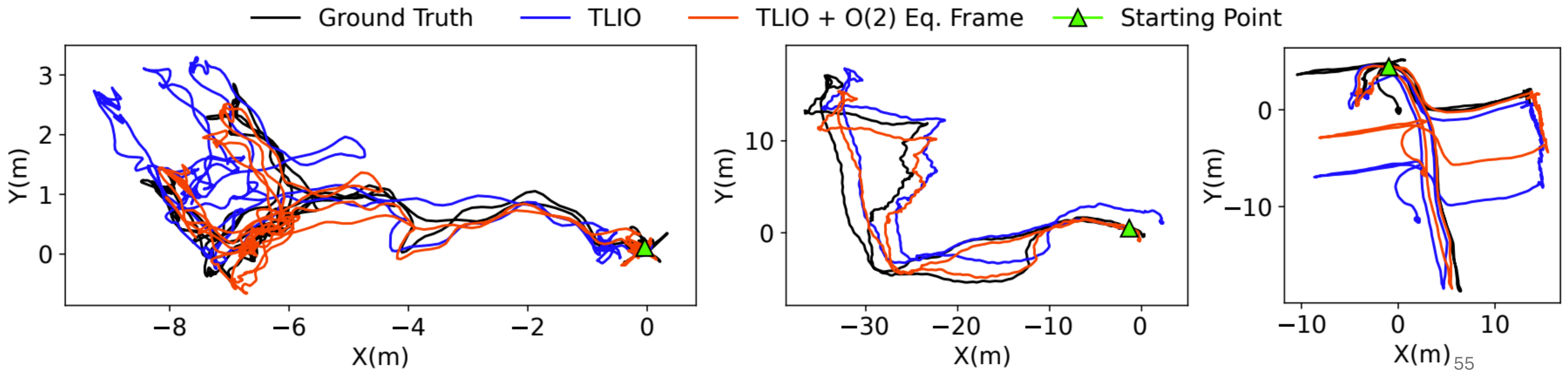
Model (RONIN)	RONIN-U ATE* (m)	RONIN-U RTE* (m)	RONIN-S ATE* (m)	RONIN-S RTE* (m)	RIDI-T ATE* (m)	RIDI-T RTE* (m)	RIDI-C ATE* (m)	RIDI-C RTE* (m)	OxIOD ATE* (m)	OxIOD RTE* (m)
+ 100% data	5.14	4.37	3.54	2.67	1.63	1.91	1.67	1.62	3.46	4.39
+ 50% data †	5.57	4.38	-	-	1.19	1.75	-	-	3.52	4.42
+ 50% data + J †	5.02	4.23	-	-	1.13	1.65	-	-	3.59	4.43
+ 50% data + TTT †	5.05	4.14	-	-	1.04	1.53	-	-	2.92	3.67
+ 50% data + J +TTT †	5.07	4.17	-	-	1.03	1.51	-	-	2.96	3.74
+ 50% data + **SO(2) Eq. Frame**	5.18	4.35	3.67	2.72	0.86	1.59	0.63	1.39	1.22	2.39
+ 50% data + **O(2) Eq. Frame**	4.42	3.95	3.32	2.66	0.82	1.52	0.70	1.41	1.28	2.10
Naive Double Integration (NDI)	458.06	117.06	675.21	1.6948	31.06	37.53	32.01	38.04	1941.41	848.55

Application to TLIO

- Adding our **EqNIO** to TLIO consistently improves results!

* Indicates NN results

Model	TLIO Dataset MSE* ($10^{-2}m^2$)	ATE (m)	ATE* (m)	RTE (m)	RTE* (m)	AYE (deg)	Aria Dataset MSE* ($10^{-2}m^2$)	ATE (m)	ATE* (m)	RTE (m)	RTE* (m)	AYE (deg)
TLIO	3.333	1.722	3.079	0.521	0.542	2.366	15.248	1.969	4.560	0.834	0.977	2.309
+ rot. aug.	3.242	1.812	3.722	0.500	0.551	2.376	5.322	1.285	2.103	0.464	0.521	2.073
+ SO(2) Eq. Frame	3.194	1.480	2.401	0.490	0.501	2.428	2.457	1.178	1.864	0.449	0.484	2.084
+ O(2) Eq. Frame	2.982	1.433	2.382	0.458	0.479	2.389	2.304	1.118	1.850	0.416	0.465	2.059



Conclusion

- We introduce a robust and generalizable canonicalization scheme for NDPs.
- We formalize the group actions of gravity-preserving roto-reflection on IMU measurements.
- By reducing the data variability seen by neural networks these frames boost the generalization of existing networks and enforce exact equivariance.
- This work paves the way for robust, and low-drift odometry running on edge devices.

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