Learning IMU Bias with Diffusion Model

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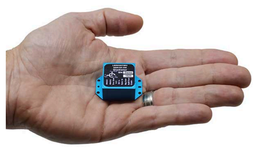
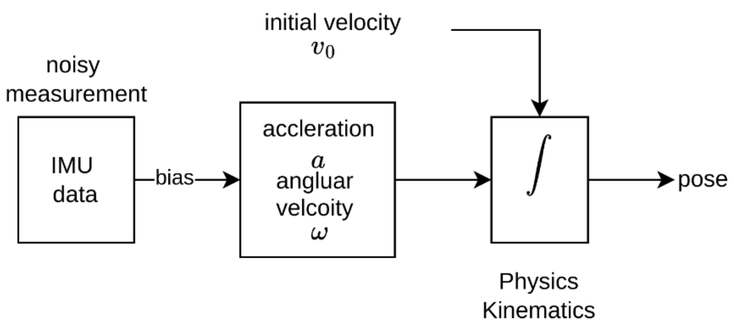
Motivation



- IMU is a portable low cost sensor that measures motion
- Time varying bias corrupts data, so IMU can't work on its own
- Bias is hard to model analytically
- Can we learn bias from data, so that we can navigate with IMU only?

IMU bias modeling: Necessity & Challenge



- Bypassing IMU bias modeling to predict pose requires predicting initial velocity. This is only possible for patterned motion
- For general motion, we have to model IMU bias
- Currently, network that learns IMU bias can do well on the task where supervision is provided:

	Predicted Bias Quality	Predicted Pose Quality
Direct supervision (use GT bias)	good	bad
Indirect supervision (use GT pose)	bad	good

Contribution

- Propose a probabilistic formulation of IMU bias learning:
  1. It has better performance than existing regression-based methods
  2. It has good pose quality and bias quality at the same time

- Design a lightweight diffusion model to realize the formulation

check out our project page with paper and code

Probablistic Formulation

- Regression: treat bias as fixed value $\begin{bmatrix}\mathbf{b_g}(t)\\ \mathbf{b_a}(t)\end{bmatrix}$ ✗
- We treat bias as conditional probability distribution

$$\text{network}(\boldsymbol{\omega_m}, \mathbf{a_m}) \longrightarrow p(\mathbf{b_g}, \mathbf{b_a} | \boldsymbol{\omega}, \mathbf{a})$$ ✓

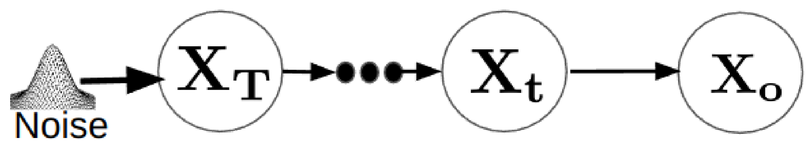
Diffusion Model

powerful generative model that can encode complex data x_0 with latent code x_1 ... x_T

Train: from x_0 to x_T

$$\mathbf{x}_t = \sqrt{1-\beta_t}\mathbf{x}_{t-1} + \sqrt{\beta_t}\epsilon_{t-1}, \epsilon_{t-1} \sim \mathcal{N}(0,1)$$

denoiser network $\hat{\epsilon}_{t-1} = \epsilon_\theta(\mathbf{x}_t, t, \mathbf{c})$

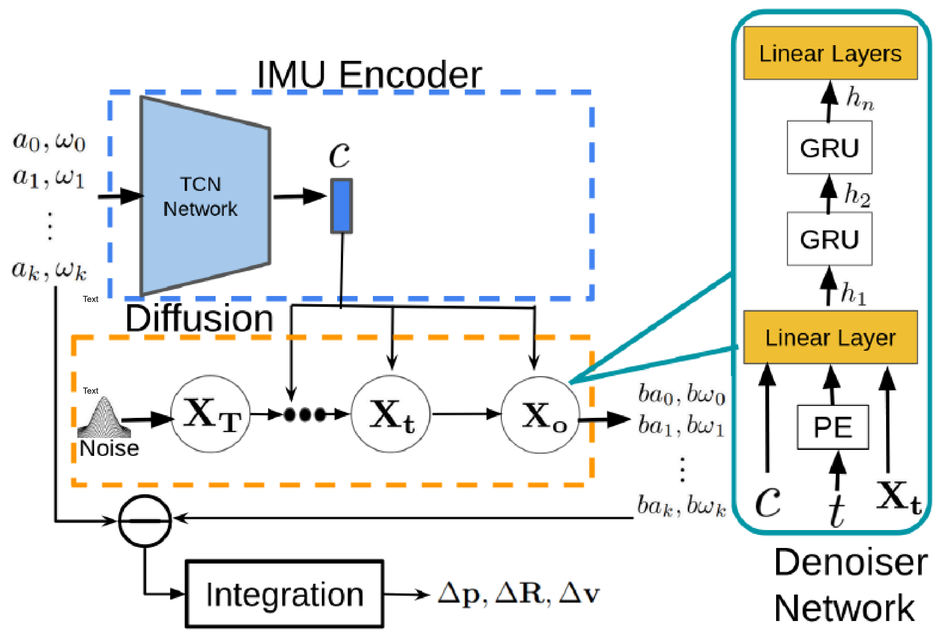


Inference: from x_T to x_0

$$\mathbf{x}_{t-1} = \frac{1}{\sqrt{1-\beta_t}}(\mathbf{x}_t - \gamma_t\epsilon_\theta(\mathbf{x}_t, t)) + \sigma_t z, z \sim \mathcal{N}(0, I)$$

After training, inferred x_0 can capture complex data distribution

Network Design



- TCN to extract IMU feature

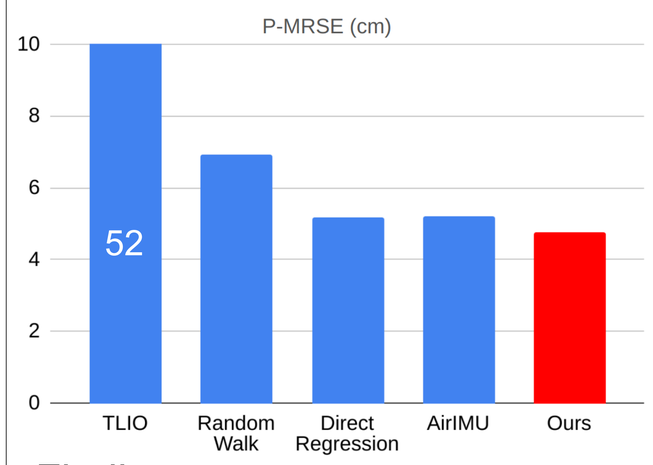
- 2-layer GRU for denoiser network in Diffusion Model

- DDPM sampler for training, DDIM sampler for inference

- Inference time: 145ms on Jetson AGX Orin

Experiment: performance

On drone dataset EuRoC



Finding:

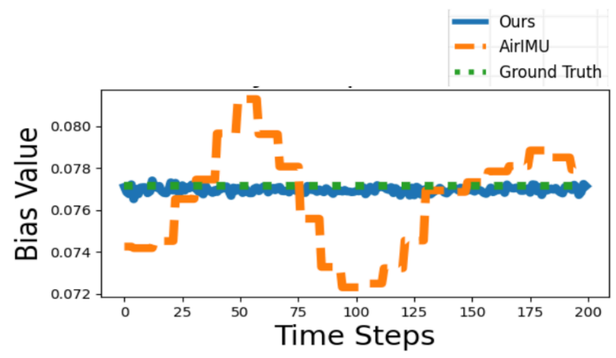
1. As drone is highly dynamic, there is no motion pattern, so bypassing IMU bias results in bad performance (TLIO)

2. Our method achieves similar performance to SoTA IMU bias modeling method using indirect supervision (AirIMU)

3. Our method is better than regression based method with direct supervision

4. Our method is better than classical random walk modeling

Experiment: bias prediction quality



Our model produces more faithful bias prediction to GT than AirIMU

Our probabilistic formulation of IMU bias learning using diffusion model opens up new opportunity to capture IMU bias with direct supervision