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Region-Selective Synthetic Data Injection for Data-Driven Magnetic Capsule Pose Estimation

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Abstract— **Accurate Wireless Magnetic Capsule (WCE) pose estimation remains a challenge for advancing minimally invasive medical procedures, because the relationship between magnetic sensor measurements and capsule pose is highly nonlinear and sensitive to noise and modeling errors, making large-scale training data essential for data-driven estimation. However, data acquisition itself remains a limiting factor, restricting both the volume of training data and the effective workspace of the system. To address this limitation, we propose a region-selective synthetic data injection strategy that generates additional data points using a calibrated physics-based model. In this strategy, regions with high model fidelity are replaced with physics-based data at arbitrary points, while regions with lower fidelity rely on sensor data, which provides a more accurate representation of the real system. Experimental results show that the proposed strategy achieves performance comparable to that of a purely data-driven model while significantly reducing the data acquisition burden.**

I. Introduction

Wireless Magnetic Capsule (WCE) estimation pose remains a limitation in the advancement of minimally invasive medical systems, particularly for gastrointestinal diagnostics. Accurate estimation of the capsule pose is essential to enable precise active control. Most existing actuation system such as OctoMag [1] rely on vision-based feedback; however, camera-based approaches are not feasible due to their inability to penetrate human tissue. Magnetic field sensing systems have emerged as a promising system, offering off-board sensing, feasibility, and robustness. Nevertheless, the non-linearity of the magnetic field, noise and uncertainties poses challenges for accurate pose reconstruction.

Previously, we investigated permanent magnet pose estimation using a Physics-Guided Neural Network (PGNN) [2]. Although the system demonstrated satisfactory results with position error of 1.05 ± 0.44 mm and orientation error of $2.65 \pm 0.88°$, several limitations were present. First, the sensing system relies on a robotic manipulator, resulting in a long collection time. Consequently, the dataset size is limited, which restricts the local sensor workspace coverage and potentially reduces the estimation capability.

To address this limitation, we propose a region-selective synthetic data injection strategy for PGNN training. By utilizing a calibrated physics-based model that is similar to the sensor measurements, synthetic data can be generated for arbitrary poses without the use of physical systems. However, model mismatch can degrade the data-driven learning process. Therefore, the data generation should be restricted to regions where the model accuracy is high compared with the sensor measurements. This approach reduces data collection time while increasing dataset size, thereby improving training efficiency and workspace coverage.

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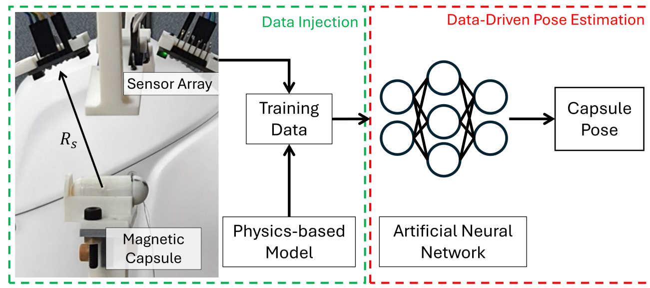


Fig. 1: Framework of the data-injection for magnetic capsule pose estimation

II. Region-Selective Synthetic Data Injection

A. Point-Dipole Approximation

Magnetic field strength (B-field) at point r can be calculated using a simplified B-field model known as Point-Dipole Approximation (1).

$$\mathbf{B}(r) = \frac{\mu_0}{4\pi}\left[\frac{3(\mathbf{m}\cdot\hat{r})\hat{r}}{r^5} - \frac{\mathbf{m}}{r^3}\right] \tag{1}$$

where μ_0 is permeability of air, $\mathbf{m}$ is the dipole moment of the permanent magnet, and $\hat{r}$ is the unit vector of r. Using this simplified equation, the magnetic field can be efficiently estimated. However, this approximation breaks down when the distance between the permanent magnet and the point r becomes sufficiently small. In this region, higher-order terms and physical misalignment can no longer be neglected, leading to decreasing model accuracy.

To prevent model mismatch in regions where the model approximation degrades, a physics-based model can be replaced by a data-driven model that implicitly captures the higher-order effects without imposing additional computation complexity. The combination of these two regions will preserve a high-quality dataset without additional data acquisition steps. Furthermore, due to model calibration, the transition boundary between physics-based and data-driven models is negligible, thereby maintaining continuity in the training data. The framework is shown in Fig. 1

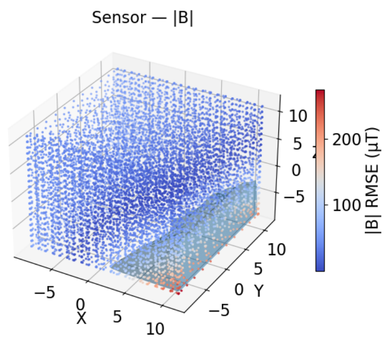


Fig. 2: Model calibration - RMSE between model value and sensor measurements (threshold $70\,\mu T$)

B. Model Calibration and Region Selection

Calibration is a vital step to preserve dataset quality. Although it requires sensor data, precise region estimation is not required; sparse sampling is sufficient to roughly identify the region. Once the region is determined, sensor data point density can be increased to enhance the pose estimation performance. Since the sensors are placed at a specific angle, (1) should undergo a kinematics transformation to match the sensor frame as $\mathbf{B}_s = R_s \cdot \mathbf{B}(r)$. where $\mathbf{B}_s$ is the magnetic field of the magnet in the sensor frame, and R_s is the rotation matrix that transforms the magnetic field from the magnet frame to the sensor frame. To find the matching accuracy between the equation-based model and sensor readings, Root Mean Square Error (RMSE) is deployed.

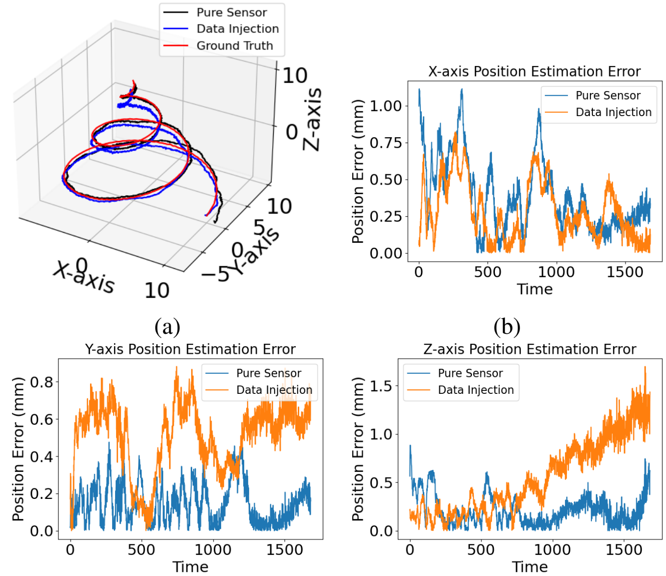
The calibration result is shown in Fig. 2, which shows the boundary between high- and low-accuracy regions, with the low-accuracy region shaded. The low accuracy region is determined via linear interpolation based on a specified threshold. In this study, the operating region is around $1.4 \times 10^3\,\mu\mathrm{T}$. To maintain an error within 5%, the corresponding threshold is approximately $70\,\mu\mathrm{T}$.

III. Experiment and Results

To ensure the data injection does not degrade the estimation performance, an offline test is conducted. In this setup, the sensor region is required to follow an inverted spiral trajectory. The performance of the synthetic data-injected model is then compared with a purely data-driven model.

Figure 3 illustrates the performance of both models trained using pure sensor measurements and our proposed strategy. Both models were able to estimate the position of the inverted spiral trajectory accurately, as shown in Fig. 3a. As indicated by Fig. 3b, both strategies have similar performance on X-axis estimation with RMSE of 0.38 mm and 0.28 mm for pure sensor measurements and our proposed strategy. However, Fig. 3c and Fig. 3d reveal lowered performance of the proposed strategy, particularly in the physics-based region, with Y-axis RMSE increases to 0.53 mm compared to 0.18 mm from the pure sensor measurements. Similarly, Z-axis RMSE rises to 0.63 mm from 0.26 mm.

The lowered performance in the physics-based model region is expected due to unmodeled uncertainty that exists in the real system. Overall, the proposed strategy was able



(a) (b)

(c) (d)

Fig. 3: Experiment result of the data-injected model. (a) 3D trajectory visualization. (b) Position error in Cartesian coordinates.

to enhance the efficiency and scalability of the training process while maintaining high-precision estimation for safety-critical applications.

IV. Conclusion

The proposed strategy improves the efficiency and scalability of the ANN training process by significantly reducing data acquisition time while preserving acceptable accuracy for safety-critical applications. Furthermore, the calibrated physics-based model effectively substitutes for regions in which the model accuracy is high, thereby minimizing the need for additional data acquisition.

In this work, the proposed strategy has been validated only for position estimation. Future work will extend this strategy to full pose estimation problem, including the orientation of the magnetic capsule.

References

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