

Challenges Towards Active Sampling for Online AI Model Refinement

1st Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

2nd Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

3rd Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

4th Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

5th Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

6th Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

Abstract—AI models deployed in real-world tasks (e.g., surveillance, implicit mapping, health care) typically need to be refined for better modelling of the changing real-world environments and various online refinement methods (e.g., domain adaptation, few shot learning) are proposed for refining the AI models based on sampled training input from the real world. However, in the whole loop of AI model online refinement, there is a section rarely discussed: sampling of training input from the real world. In this paper, we show from the perspective of online refinement of AI models deployed on edge devices (e.g., robots) that several challenges in sampling of training input are hindering the effectiveness (e.g., final training accuracy) and efficiency (e.g., online training accuracy gain per epoch) for the online refinement process. Notably, the online refinement relies on training input consecutively sampled from the real world and suffers from locality problem: the consecutive samples from nearby states (e.g., position and orientation of a camera) are too similar and would limit the training efficiency; on the other hand, while we can choose to sample more about the inaccurate samples to better final training accuracy, it is costly to obtain the accuracy statistics of samples via traditional ways such as validating, especially for AI models deployed on edge devices. These findings aim to raise research effort for practical online refinement of AI models, so that they can achieve resiliently and sustainably high performance in real-world tasks.

I. INTRODUCTION

Online Artificial Intelligence (AI) model refinement refers to real-time training a pre-trained AI model on training inputs consecutively sampled from the real world for various edge AI applications (e.g. transportation, human language processing, implicit SLAM) deployed on edge devices (e.g., mobile phones, robots), so that the model can adapt to changing real-world environments and retain high performance. Various online refinement methods have been proposed (e.g., domain adaptation, few shot learning) in pursuit of high training accuracy, but an important section of online AI model refinement is rarely discussed: sampling of the training input from the real world. While the sampling process was traditionally completed manually, automating the process with active sampling in

reaction to real-time training statistics has the potential to further boost training accuracy, beside saving human labor.

Active sampling can be traced back to the problem of active simultaneous localization and mapping (SLAM). In active SLAM, a robot automatically decides its sampling destination (active sampling) in real-time reaction to estimated localization quality and mapping quality: either refines its localization at low localization accuracy or refines mapping of areas at low mapping accuracy. Instead of aimlessly circulating, active sampling in active SLAM boosts both mapping speed and accuracy. For online refinement, enabling active sampling has the potential to achieve both high *training effectiveness* (e.g., final training accuracy) and high *training efficiency* (e.g., online training accuracy gain per epoch) by automatically sampling areas of high potential training accuracy gain and avoiding those low.

Although active SLAM methods shed light on the design of active sampling for online AI model refinement, in this paper, we show that several challenges are hindering the training effectiveness and training efficiency in active sampling for online refinement, which is due to a key difference that AI training process is probabilistic and implicit, different from traditional deterministic and explicit SLAM process.

First, we observed low training efficiency during the consecutive sampling and named it the locality problem: while the edge device is moving around local state space (e.g., nearby position and orientation), the consecutive samples are often too similar, limiting training accuracy gain between consecutive samples. As shown in Fig.1 about the training accuracy gain around a place of interest of an implicit SLAM (building dense 3D map via online AI model refinement) task, there is a lowland of training accuracy gain around the starting state of the robot. To complete sampling of an area of interest, the robot has to sample around in the lowland of training accuracy gain, leading to low training efficiency. In our evaluation, compared with consecutive samples, TODO [10]% of the key

samples selected from the consecutive samples achieved the same level of final training accuracy, implying TODO [90]% of the samples were wasted due to the locality problem.

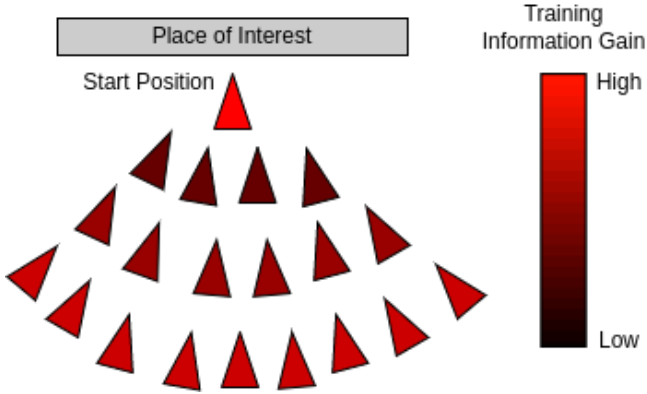


Fig. 1: Locality problem causes a lowland of training accuracy gain around the starting state

Second, real-time estimation of potential training accuracy gain of the training AI model for real-time active sampling decision making is difficult. While traditional SLAM tasks have an explicit representation (a map) that can be easily estimated for decision making, the estimation of accurate potential training accuracy gain in AI training is yet an open problem. An approximate way to quantify potential training accuracy gain is to validate training samples and those with low training accuracy have high potential training accuracy gain. But it is too computation-intensive for edge devices and easily breaks the control loop. We evaluated that the validation of the training accuracy in an implicit SLAM task typically takes TODO [30] to TODO [60] seconds and the robot has to wait for such a long time before each decision making.

In this paper, we take the first step to reveal and evaluate the challenges hindering the active sampling for online AI model refinement from achieving both high training effectiveness and high training accuracy in both quality and quantity. These findings aim to raise research effort for practical active sampling for online refinement of AI models, so that they can achieve resiliently and sustainably high performance in real-world tasks. As we are borrowing the idea of active sampling from active SLAM, we choose implicit SLAM as the main evaluation item for simplicity since implicit SLAM shares a similar task with active SLAM. The rest of the paper is organized as follows: the second chapter provides background; the third chapter describes in detail about the challenges and the estimation methodology; the final chapter concludes.

II. BACKGROUND

Online AI Model Refinement. Machine learning (ML) approaches are generally trained for a specific task on a dedicated training set. However, in many real-world applications, Labeling datasets are very expensive, and the data distributions can differ or even change over time. Therefore, Some unsupervised methods are proposed to learn knowledge from unlabeled

data and make the machine learning model to adapt the new dynamic environment. For example, dynamic unsupervised domain adaptation methods [1] is proposed to adapt a pretrained model to a new environment by training it with both unlabeled data from the dynamic environment.

With the rapid development of such methods, robots can adapt their pretrained models to new scenarios(e.g., domain shifts or changing data distributions) after training with online collected data to retain the high accuracy of the models. As another example, neural implicit representations have recently become popular in simultaneous localization and mapping (SLAM), especially in dense visual SLAM. This method enables high-fidelity and dense 3D scene reconstruction by collecting unlabeled image sequences with RGB-D sensors in real-time. We envision the prosperity of these multi-robot collaborations and unsupervised learning methods are making online training on real-time collected data on multi-robot realistic.

Dense Visual SLAM. Visual SLAM is an online approach that incrementally creates the map of an environment while localizing the robot within it. Meanwhile, it is an area that has received much attention in both industry and academia. Specifically, sparse visual SLAM algorithms estimate accurate camera poses and only have sparse point clouds as the map representation, While sparse visual SLAM algorithms estimate accurate camera poses and only have sparse point clouds as the map representation, dense visual SLAM approaches focus on recovering a dense map of a scene, which makes the method very suitable for 3D reconstruction. Dense tracking and mapping (DTAM), proposed by Newcombe et al. [2], was the first fully direct method in the literature.

Neural Implicit-based SLAM. Neural implicit representations [3] have shown great performance in many different tasks, including 3D reconstruction [4]–[7], scene completion [8]–[10], novel view synthesis [11]–[15], etc. In terms of SLAM-related applications, some works [16], [17] try to jointly optimize a neural radiance field and camera poses, but they are not suitable for large objects or wide range of camera motion. In addition, some recent works [18], [19] can support large-scale mapping, but they mainly rely on state-of-the-art SLAM systems like ORB-SLAM to obtain accurate camera poses, and do not produce 3D dense reconstruction.

NICE-SLAM [20] and iMAP [21] are the most famous two SLAM pipelines using neural implicit representations for both mapping and camera tracking. Since iMAP uses a single MLP as the scene representation so they are only adapt to small scenes, whereas NICE-SLAM, which uses hierarchical feature grids and small MLPs as the scene representation, can scale up to considerably bigger interior spaces. Nevertheless, it calls for RGB-D inputs, which restricts their use in outdoor settings or when only RGB sensors are available. In order to solve this problem, a new work named NICER-SLAM [22] was proposed, which is the first dense RGB-only SLAM, optimizes mapping and tracking end-to-end and also allows the high-quality synthesis of new views.

Active Mapping/SLAM. In the interest of exploring the

environment by planning the path of mobile robots, active SLAM combines SLAM with path planning. This improves and speeds up the SLAM algorithm's ability to produce high-precision maps. The three active vision issues (localization, mapping, and planning) are combined by active SLAM. Robots can now autonomously carry out localization and mapping tasks, which helps to improve the accuracy of both those tasks and the representation of the environment. This topic has been studied before [23] came up with the phrase "Active SLAM," mostly as known as "exploration problems" [24], [25].

Specifically, iRotate [26] offers an active visual SLAM approach for omnidirectional robots because the static camera restricts the freedom of visual information acquisition. During the path execution, the robot can actively and continuously control its camera heading to maximize the environment coverage by taking advantage of its omnidirectional nature. The robot can significantly speed up the information-gathering process and quickly reduce the level of map uncertainty by actively performing coverage. In particular, these methods need to explicitly build maps before they can work, so they cannot be directly applied to the implicit SLAM framework. At the same time, the memory overhead of building explicit maps is large, and the lack of memory resources of robots often cannot support such active SLAM methods.

III. CHALLENGES TOWARDS ACTIVE SAMPLING

This section explores the challenges towards active sampling for online AI model refinement in both quality and quantity. We use a state-of-the-art implicit method, NICE SLAM as our main evaluation item and integrates it as a ROS package...

A. Locality

B. Estimation of Potential Training Accuracy Gain

C. Others

TODO [Cost of distributed training]

IV. CONCLUSION

TODO [conclusion]

REFERENCES

- [1] Q. Tian, Y. Zhu, H. Sun, S. Chen, and H. Yin, "Unsupervised domain adaptation through dynamically aligning both the feature and label spaces," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 12, pp. 8562–8573, 2022.
- [2] R. A. Newcombe, S. J. Lovegrove, and A. J. Davison, "Dtam: Dense tracking and mapping in real-time," in *2011 international conference on computer vision*. IEEE, 2011, pp. 2320–2327.
- [3] B. Mildenhall, P. P. Srinivasan, M. Tancik, J. T. Barron, R. Ramamoorthi, and R. Ng, "Nerf: Representing scenes as neural radiance fields for view synthesis," *Communications of the ACM*, vol. 65, no. 1, pp. 99–106, 2021.
- [4] L. Mescheder, M. Oechsle, M. Niemeyer, S. Nowozin, and A. Geiger, "Occupancy networks: Learning 3d reconstruction in function space," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2019, pp. 4460–4470.
- [5] J. J. Park, P. Florence, J. Straub, R. Newcombe, and S. Lovegrove, "Deepsdf: Learning continuous signed distance functions for shape representation," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2019, pp. 165–174.

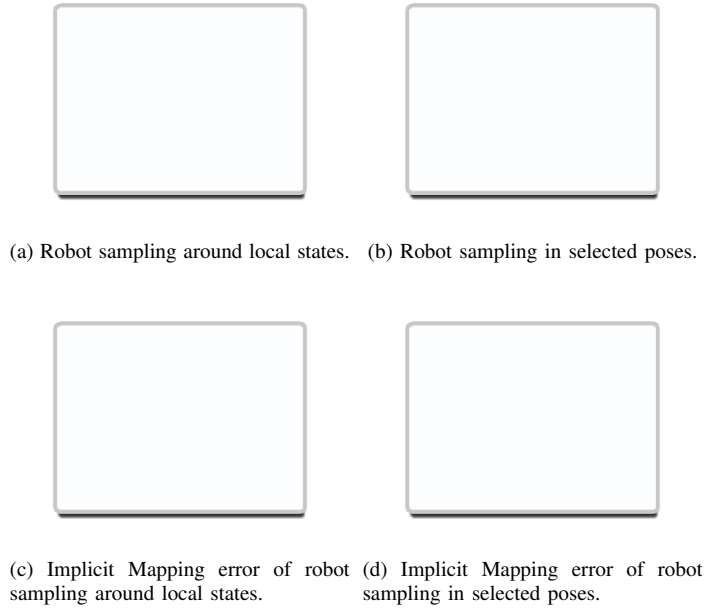


Fig. 2: Sampling poses and mapping error against sampling times.



Fig. 3: Time consumption validating Implicit SLAM model with various model sizes and number of samples

- [6] S. Peng, C. Jiang, Y. Liao, M. Niemeyer, M. Pollefeys, and A. Geiger, "Shape as points: A differentiable poisson solver," *Advances in Neural Information Processing Systems*, vol. 34, pp. 13 032–13 044, 2021.
- [7] S. Liu, Y. Zhang, S. Peng, B. Shi, M. Pollefeys, and Z. Cui, "Dist: Rendering deep implicit signed distance function with differentiable sphere tracing," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 2019–2028.
- [8] S. Peng, M. Niemeyer, L. Mescheder, M. Pollefeys, and A. Geiger, "Convolutional occupancy networks," in *Computer Vision–ECCV 2020: 16th*



Fig. 4: Time composition using distributed training with various model sizes

European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part III 16. Springer, 2020, pp. 523–540.

- [9] S. Lionar, D. Emtsev, D. Svilarkovic, and S. Peng, “Dynamic plane convolutional occupancy networks,” in *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 2021, pp. 1829–1838.
- [10] C. Jiang, A. Sud, A. Makadia, J. Huang, M. Nießner, T. Funkhouser *et al.*, “Local implicit grid representations for 3d scenes,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 6001–6010.
- [11] C. Reiser, S. Peng, Y. Liao, and A. Geiger, “Kilonerf: Speeding up neural radiance fields with thousands of tiny mlps,” in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2021, pp. 14 335–14 345.
- [12] R. Martin-Brualla, N. Radwan, M. S. Sajjadi, J. T. Barron, A. Dosovitskiy, and D. Duckworth, “Nerf in the wild: Neural radiance fields for unconstrained photo collections,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2021, pp. 7210–7219.
- [13] M. Tancik, V. Casser, X. Yan, S. Pradhan, B. Mildenhall, P. P. Srinivasan, J. T. Barron, and H. Kretschmar, “Block-nerf: Scalable large scene neural view synthesis,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 8248–8258.
- [14] A. Pumarola, E. Corona, G. Pons-Moll, and F. Moreno-Noguer, “D-nerf: Neural radiance fields for dynamic scenes,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2021, pp. 10 318–10 327.
- [15] D. Verbin, P. Hedman, B. Mildenhall, T. Zickler, J. T. Barron, and P. P. Srinivasan, “Ref-nerf: Structured view-dependent appearance for neural radiance fields,” in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2022, pp. 5481–5490.
- [16] S.-F. Chng, S. Ramasinghe, J. Sherrah, and S. Lucey, “Gaussian activated neural radiance fields for high fidelity reconstruction and pose estimation,” in *Computer Vision—ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XXXIII*. Springer, 2022, pp. 264–280.
- [17] R. Clark, “Volumetric bundle adjustment for online photorealistic scene capture,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 6124–6132.
- [18] C.-M. Chung, Y.-C. Tseng, Y.-C. Hsu, X.-Q. Shi, Y.-H. Hua, J.-F. Yeh, W.-C. Chen, Y.-T. Chen, and W. H. Hsu, “Orbeez-slam: A real-time monocular visual slam with orb features and nerf-realized mapping,” *arXiv preprint arXiv:2209.13274*, 2022.
- [19] A. Rosinol, J. J. Leonard, and L. Carlone, “Nerf-slam: Real-time dense monocular slam with neural radiance fields,” *arXiv preprint arXiv:2210.13641*, 2022.
- [20] Z. Zhu, S. Peng, V. Larsson, W. Xu, H. Bao, Z. Cui, M. R. Oswald, and M. Pollefeys, “Nice-slam: Neural implicit scalable encoding for slam,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 12 786–12 796.
- [21] E. Sucar, S. Liu, J. Ortiz, and A. J. Davison, “imap: Implicit mapping and positioning in real-time,” in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2021, pp. 6229–6238.
- [22] Z. Zhu, S. Peng, V. Larsson, Z. Cui, M. R. Oswald, A. Geiger, and M. Pollefeys, “Nicer-slam: Neural implicit scene encoding for rgb slam,” *arXiv preprint arXiv:2302.03594*, 2023.
- [23] A. Davison and D. Murray, “Simultaneous localization and map-building using active vision,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 865–880, 2002.
- [24] C. Stachniss, D. Hahnel, and W. Burgard, “Exploration with active loop-closing for fastslam,” in *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)(IEEE Cat. No. 04CH37566)*, vol. 2. IEEE, 2004, pp. 1505–1510.
- [25] J. Moody, S. Hanson, and R. Lippmann, “Active exploration in dynamic environments,” in *Advances in Neural Information Processing Systems 4*. Citeseer, 1992.
- [26] E. Bonetto, P. Goldschmid, M. Pabst, M. J. Black, and A. Ahmad, “irotate: Active visual slam for omnidirectional robots,” *Robotics and Autonomous Systems*, vol. 154, p. 104102, 2022.