**ARAP Scholarship**

We have a joint scholarship between the University of Surrey and A\*STAR, supervised by Prof. [Xiatian Zhu](https://surrey-uplab.github.io/) and Dr. [Xun Xu](https://alex-xun-xu.github.io/). Candidates with a strong track record are welcome to apply. Details can be found at [ARAP](https://www.a-star.edu.sg/Scholarships/for-graduate-studies/a-star-research-attachment-programme).

1. **Scholarship & Application**

**Deadline:** 1st Dec 2023

**Stipend**:

Provided by A\*STAR during stay with A\*STAR. SGD$2,700 monthly stipend, airfare grant SGD$1500, settle-in allowance SGD$1000, housing allowance, conference allowance, medical insurance, etc.

Provided by Surry during stay with Surrey. xxx

**Duration**: Awarded is expected to spend 1-2 years physically in A\*STAR and 2-3 years in Surrey.

1. **Objective and Project Description**

**Title:** Towards Realistic On-the-Fly Test-Time Adaptation for Robotic Perception

**Abstract:** Deploying robotic arms is key to the manufacturing and logistic industries of Singapore. Current robotic arms often work only in restricted environments [1]. Applying robot arm to interact with open requires perception of environment, e.g. identifying the spatial extent and pose of objects, and the state-of-the-art methods use deep learning (DL) methods. The DL models are often pre-trained on clean dataset and may not generalize to unseen testing data which could be subject to distribution shifts caused by change of product style, visual corruptions, etc. In this project, we shall explore adapting pre-trained model at test-time, tackle the challenge of continuous distribution shift, efficient adaptation from large-scale model and exploiting human intervention, and eventually demonstrate on robotic perception tasks.

***Continuous Test-Time Domain Adaptation for Robotic Perception***

Perception models are often trained on clean data collected from well-controlled lab environment or synthetic data. When models are deployed in real manufacturing or logistic environments, the data distribution could be different from the training data, e.g. due to change of lighting condition, background or products, thus posing great challenges to the algorithm. To tackle the data distribution shift challenge, domain adaptation (DA) [2] emerges as a solution which updates the model’s parameters towards target domain distribution. The existing DA approaches often assume the deep learning model can be updated with access to both source and target domain data, nevertheless, in a more realistic scenario source domain data may not be available due to storage overhead and privacy issues. More importantly the target domain data may experience distribution shift in a continuous manner, e.g. continually change lighting or background. In this WP, we aim to address domain adaptation at test-time under continuous changing target distributions with no access to source data. There are two challenges associated with this realistic test-time adaptation setting. First, it is unknown when and whether the target domain distribution has changed, hence initializing a new adapted model w.r.t. novel target domain distribution is impossible. Moreover, target domain distribution may repeat over time, a one-way adaptation only satisfies the performance requirement on the immediate target distribution, and it may sacrifice the performance on other distributions due to the forgetting issue.

***Resource-Efficient Adaptation for Robotic Perception***

Another major obstacle that prohibits the adoption of model adaptation at inference stage is the computing resource efficiency, which is becoming an increasingly important concern when end users wish to adapt large-scale AI foundation model [3]. The state-of-the-art approaches towards adapting pre-trained model to target domain data often fine-tunes the whole deep learning network parameters. Such a paradigm requires backprogating through all model weights, which is computational and memory inefficient and may become even infeasible on large-scale foundation model with hundreds of billions of parameters when end-users are not equipped with sufficient computing infrastructure. Alternative to fine-tuning the whole model, existing methods targeting high efficiency in test-time adaptation often update a subset of model weights, e.g. batchnorm parameters [4] or classifier weights [5], but this will lead to inferior adaptation performance. Therefore, we aim to explore a resource-efficient approach towards test-time adaptation of robotic perception tasks to allow end users to adapt large-scale foundation model without accessing expensive computing resources and still maintain competitive performance.

***Test-Time Adaptation with Active Human Intervention***

Adaption to target domain data at test time is expected to require minimal human intervention. However, when additional human intervention is available at inference stage, it is often desirable for human operators to provide limited annotated examples as demonstrations to guide the model update. Nevertheless, there is no trivial solutions to the above problem. First, the annotation budget is often limited as inference adaptation will mostly be adopted by small-scale end users. Moreover, as testing data is observed in a streaming fashion, limited annotation budget should be distributed across the whole course of test-time adaptation, hence, annotating redundant testing samples may result in a waste of annotation budget. In this WP, we aim to develop algorithm to automatically recommend testing samples for human annotation and propose the following approaches.

[1] C. Xie, Y. Xiang, A. Mousavian and D. Fox, “Unseen object instance segmentation for robotic environments,” IEEE Transactions on Robotics, 2021.

[2] M. Wang and W. Deng, “Deep visual domain adaptation: A survey,” Neurocomputing, 2018.

[3] A. Kirillov, E. Mintun, N. Ravi, H. Mao, C. Rolland, L. Gustafson, T. Xiao, S. Whitehead, A. C. Berg, W.-y. Lo, P. Dollar and R. Girshick, “Segment Anything,” ArXiv, 2023.

[4] D. Wang, E. Shelhamer, S. Liu, B. Olshausen and T. Darrell , “Tent: Fully-Test Time Adaptation by Entropy Minimization,” in International Conference on Learning Representations, 2021.

[5] Y. Iwasawa and Y. Matsuo, “Test-Time Classifier Adjustment Module for Model-Agnostic Domain Generalization,” in Advances in Neural Information Processing Systems, 2021.