Dynamic Retraining-Updating Mean Teacher for Source-Free Object Detection

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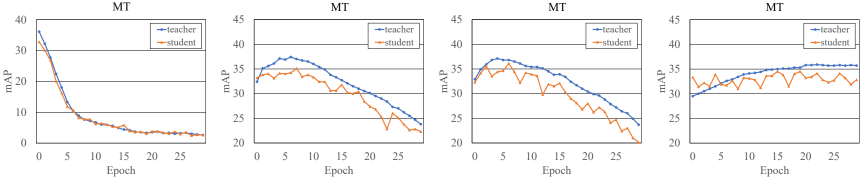
Outline

Introduction

Due to the absence of source supervision, applying the **Mean Teacher (MT)** framework in Source-Free Object Detection (SFOD) encounters significant training instability. We identify **two primary issues**:

- **Inopportune updates of the teacher model from the student model:** Uncontrolled degradation of the teacher model.
- **The student model's tendency to replicate errors from incorrect pseudo labels:** Leading to it being trapped in a local optimum.

$\rightarrow$ Both factors contribute to a detrimental circular dependency, resulting in rapid performance degradation in recent self-training frameworks.



(a) EMA weight = 0.99, stepsize = 1 (b) EMA weight = 0.999, stepsize=1 (c) EMA weight = 0.99, stepsize = 10 (d) EMA weight = 0.999, stepsize = 10

Figure: The training curves of different Mean Teacher training strategies on the validation set of Cityscapes → Foggy Cityscapes under the SFOD setting. These varied strategies consistently show a degradation phenomenon: the teacher model gradually degrades due to inappropriate updates from the student model, while the student model experiences performance deterioration due to inaccurate pseudo labels.

Our Contributions

To tackle the above challenges, we proposed:

- **Dynamic Retraining-Updating (DRU) mechanism** To actively manage the student training and teacher updating processes to achieve co-evolutionary training.
- **Historical Student Loss** To mitigate the influence of incorrect pseudo labels generated by the deteriorating teacher model.

Method Overview

Our proposed DRU method aligns with the structure of the MT framework.

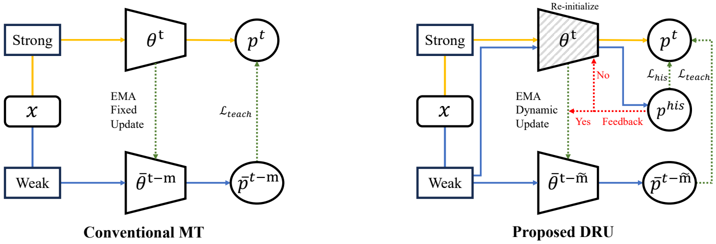


Figure: The comparison of the conventional Mean Teacher (MT) framework (*left*) and our Dynamic Retraining-Updating (DRU) method (*right*). **Left:** In MT, the teacher model is continuously updated by a fixed interval m ($m = 1$ or $m = s, (s > 1)$). **Right:** In DRU, the student model is dynamically retrained and the teacher model is dynamically updated based on prediction feedback. Additionally, the current student model is further supervised by the historical student model.

Training Process

Algorithm 1 Dynamic Retraining-Updating training process

Input: Teacher model $G_{\bar{\theta}}^{tea}$, student model G_{θ}^{stu}, unlabeled target data D_t, uncertainty feedback U, and meta-iteration M

Output: Optimized teacher model $G_{\bar{\theta}}^{tea}$

```
Empty buffer D_his; Copy G_θ^stu as G_θinit^stu; Index i = 0
for image batch x_b in D_t do
    Update G_θ^stu with x_b, G_θ̄^tea and G_θinit^stu          ▷ with Historical Student Loss
    Append x_b to D_his; i++
    if i < M then
        if U[G_θ^stu(D_his)] < U[G_θinit^stu(D_his)] then    ▷ Student evolved
            Update G_θ̄^tea with G_θ̄^tea and G_θ^stu           ▷ Teacher Dynamic Updating
            Reset D_his; Copy G_θ^stu as G_θinit^stu; i = 0
    else                                                     ▷ Student trapped in a local optimum
        Reinitialize G_θ^stu with G_θ^stu and G_θinit^stu     ▷ Student Dynamic Retraining
        Reset D_his; Copy G_θ^stu as G_θinit^stu; i = 0
return G_θ̄^tea
```

Method Architecture

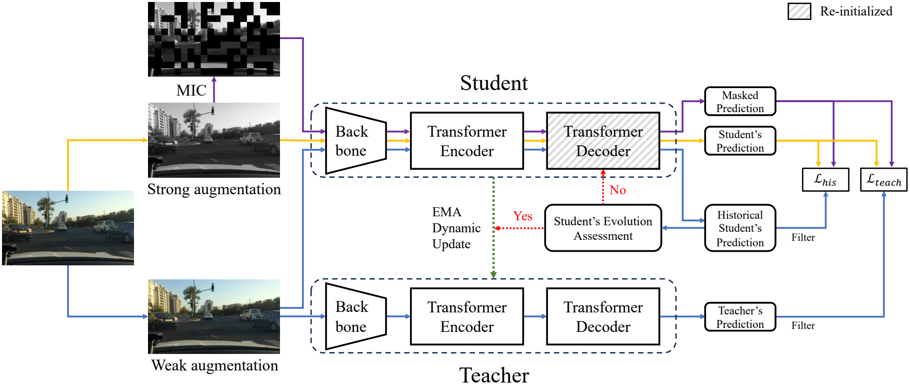


Figure: Overview of Dynamic Retraining-Updating (DRU), which is built upon the Mean Teacher framework. DRU employs dynamic retraining of the student model and dynamic updating of the teacher model based on the student's evolution assessment. The student model is further supervised by Historical Student Loss $\mathcal{L}_{his}$.

Experimental Results

	Method	Detector	city2foggy	city2bdd	sim2city
	Source Only	Deformable DETR	29.5	29.1	48.9
UDA	TDD	Faster R-CNN	43.1	33.6	53.4
	PT	Faster R-CNN	42.7	34.9	55.1
	O^2net	Deformable DETR	46.8	30.5	54.1
	MTTrans	Deformable DETR	43.4	33.7	57.9
SFOD	SED(Mosaic)	Faster R-CNN	33.5	29.0	43.1
	A^2SFOD	Faster R-CNN	35.4	31.6	44.0
	PETS	Faster R-CNN	35.9	31.3	57.8
	Ours	Deformable DETR	**43.6**	**36.6**	**58.7**

Table: Results of different UDA and SFOD methods for three benchmarks. "Source Only" refers to the source-trained model.

Modules Analysis

Src	MT	MIC	$\mathcal{L}_{his}$	DRU	mAP	gain
✓					29.5	
✓	✓				37.4	+7.9
✓	✓	✓			39.8	+10.3
✓	✓	✓	✓		41.3	+11.8
✓	✓	✓		✓	40.9	+11.4
✓	✓	✓	✓	✓	**43.6**	+**14.1**

Table: Ablation studies of adding modules to MT framework on Cityscapes → Foggy Cityscapes. "Src" denotes the Source Only trained model. "MT" represents the Mean Teacher baseline. "MIC", "$\mathcal{L}_{his}$", and "DRU" denote the Masked Image Modeling, Historical Student Loss, and Dynamic Retraining-Updating, respectively.

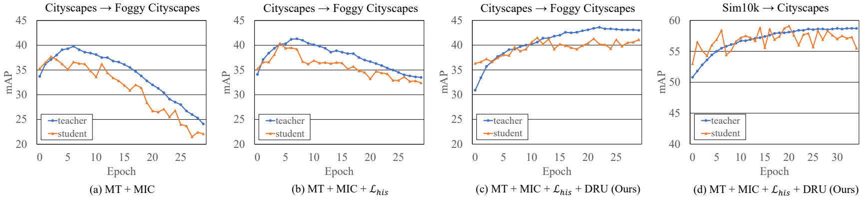


Figure: (a), (b), (c) The training curves for adding modules to MT on Cityscapes $\rightarrow$ Foggy Cityscapes. (d) The training curves of our method on Sim10k $\rightarrow$ Cityscapes.

Conclusion

- Investigate the causes of training instability of the MT framework for the SFOD.
- Propose the **Dynamic Retraining-Updating mechanism** and **Historical Student Loss**.
- DRU significantly enhances the stability and adaptability of the self-training paradigm.

Thank you!

Project page: https://github.com/lbktrinh/DRU
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