Distribution-Aware Continual Test Time Adaptation for Semantic Segmentation

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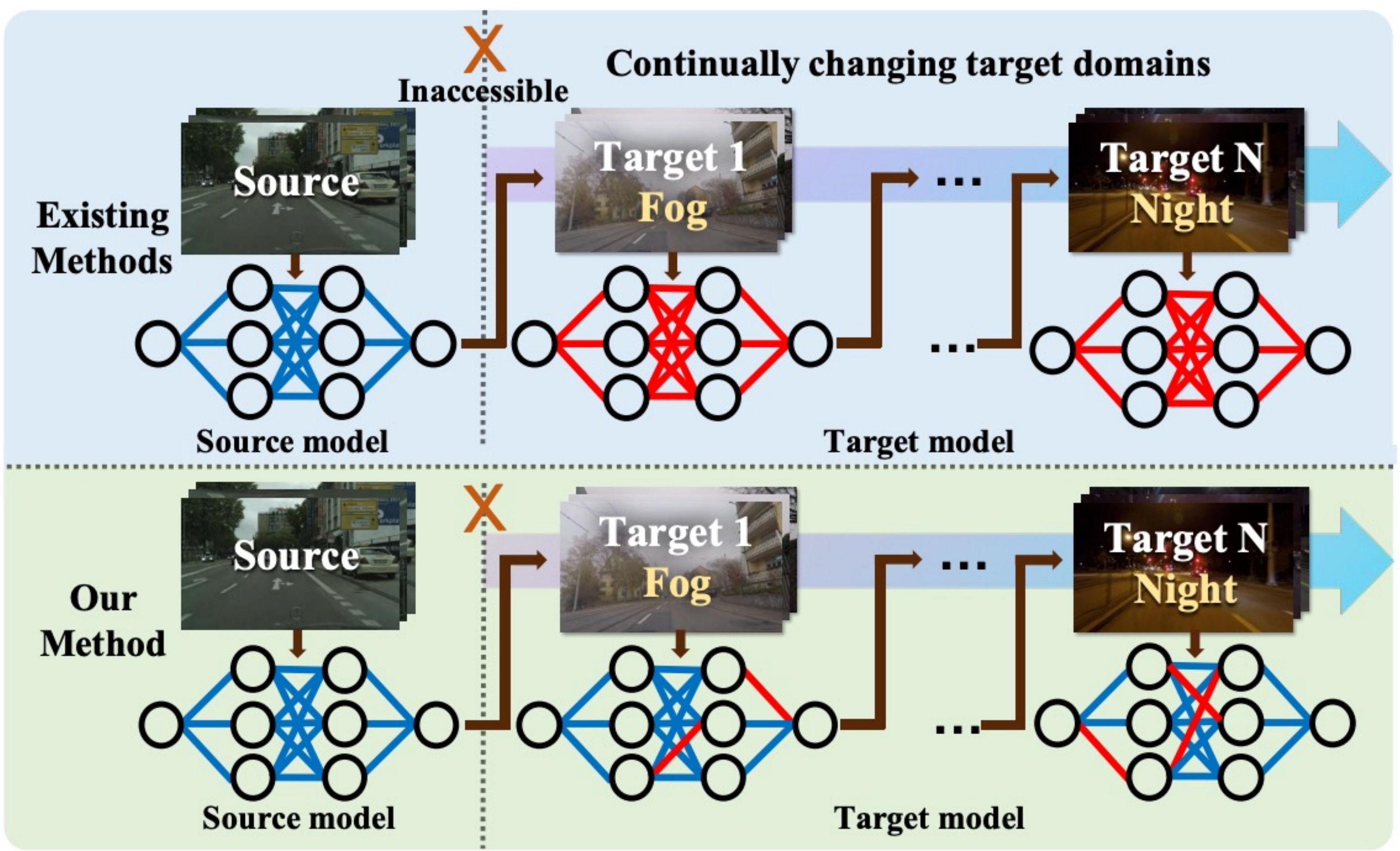
Overview



Main Contributions

1. Distribution-Aware Tuning (DAT)
- DAT adaptively select two small parameter groups: Domain-Specific Parameters (DSP) and Task-Relevant Parameters (TRP).
- Selection based on degree of distribution shifts.
- Addresses issues of error accumulation and catastrophic forgetting.

2. Parameter Accumulation Update (PAU) strategy
- At early stage, only small fraction of parameters (0.1%) selected for each sample.
- Parameters added to updated group until distribution shift is small.

3. State-of-the-art (SOTA) Performance
- Cityscape-ACDC and SHIFT continual datasets.
- Effectiveness in solving semantic segmentation CTTA problem.

Pipeline

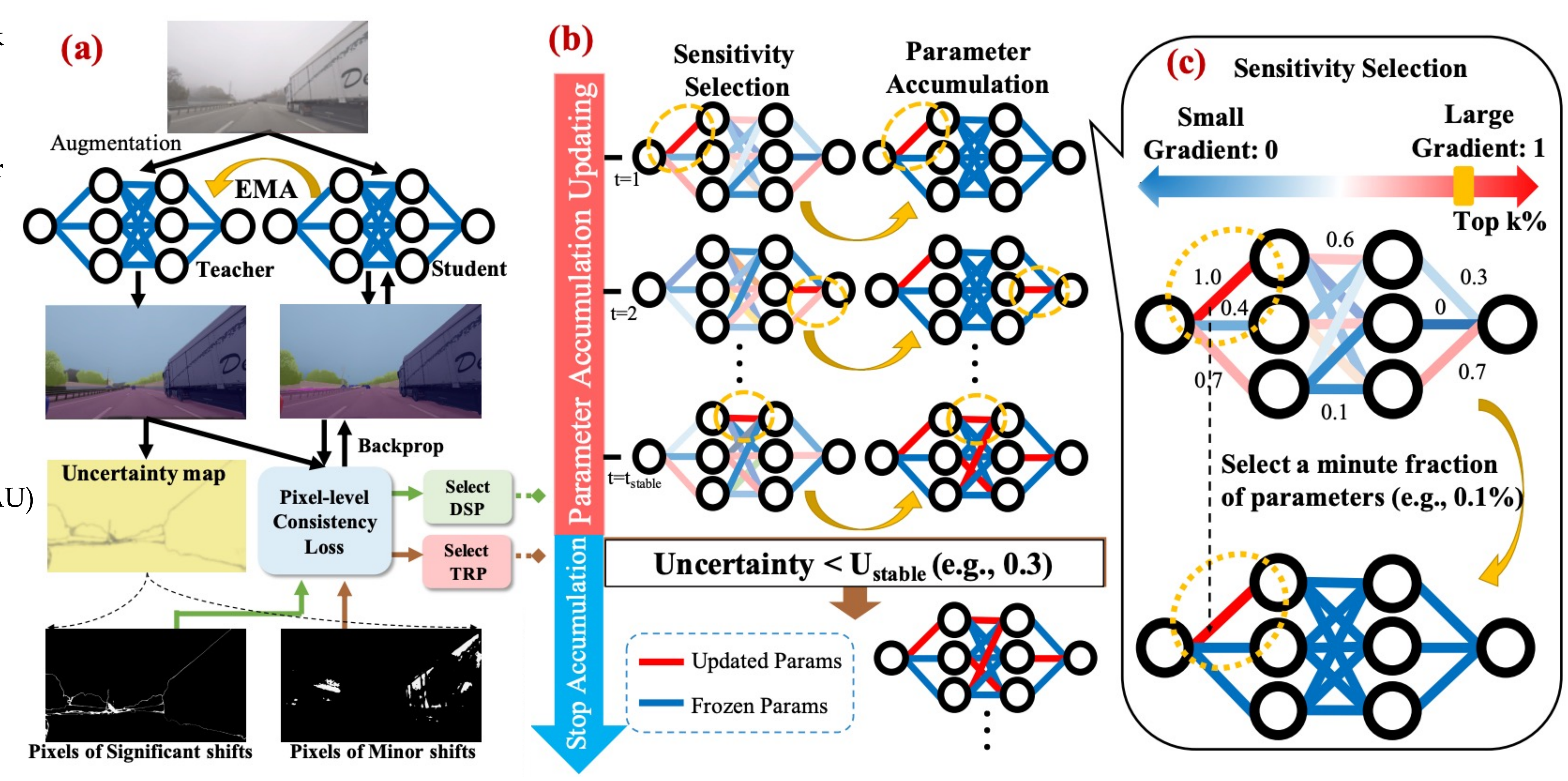
Distribution-Aware Tuning Framework

1. Teacher-student framework
- Exponential Moving Average (EMA)
- Utilizes pixel-wise consistency loss for optimization.
- Obtains uncertainty map from teacher model for distribution evaluation.

2. Parameter Selection
(a) Domain-Specific Parameters (DSP)
(b) Task-Relevant Parameters (TRP)
- Selection based on distribution shift.

3. Parameter Accumulation Update (PAU) strategy.
- Selects only a small fraction of parameters for each sample.
- Added to gathered parameter groups.

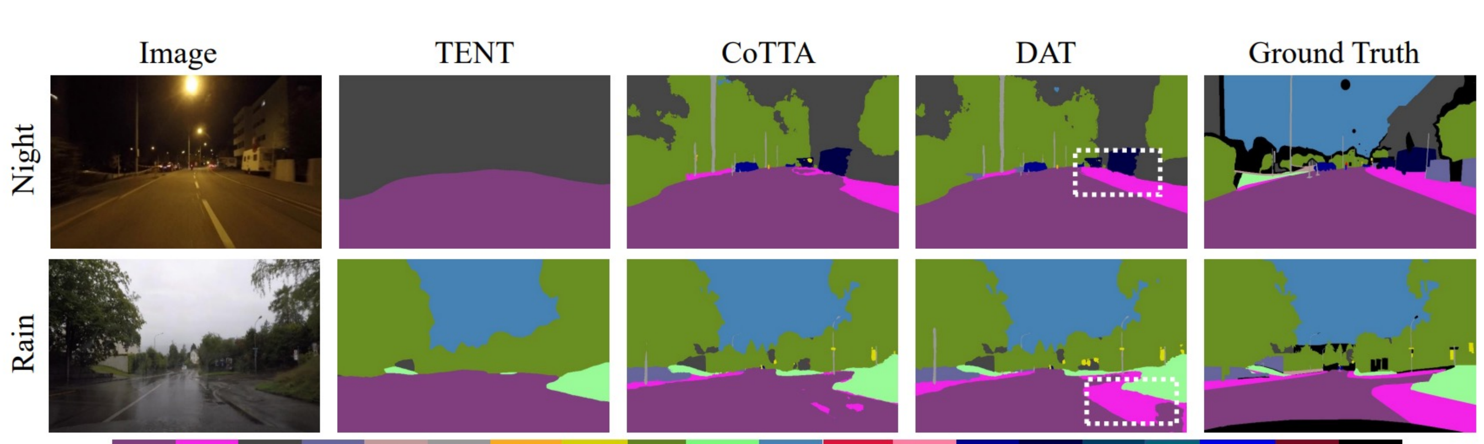
4. DSP and TRP Selection Details
- Based on gradient sensitivity.



Discussion

PERFORMANCE COMPARISON FOR CITYSCAPE-TO-ACDC CTTA. DURING TESTING, WE SEQUENTIALLY EVALUATE THE FOUR TARGET DOMAINS THREE TIMES. MEAN DENOTES THE AVERAGE MIOU SCORE. GAIN QUANTIFIES THE METHOD'S IMPROVEMENT COMPARED TO THE SOURCE MODEL.

Time		t ⟶															
Round		1					2					3					Mean↑	Gain
Method	REF	Fog	Night	Rain	Snow	Mean↑	Fog	Night	Rain	Snow	Mean↑	Fog	Night	Rain	Snow	Mean↑		
Source	NIPS2021 [29]	69.1	40.3	59.7	57.8	56.7	69.1	40.3	59.7	57.8	56.7	69.1	40.3	59.7	57.8	56.7	56.7	/
TENT	ICLR2021 [30]	69.0	40.2	60.1	57.3	56.7	68.3	39.0	60.1	56.3	55.9	67.5	37.8	59.6	55.0	55.0	55.7	-1.0
CoTTA	CVPR2022[5]	70.9	41.2	62.4	59.7	58.6	70.9	41.1	62.6	59.7	58.6	70.9	41.0	62.7	59.7	58.6	58.6	+1.9
DePT	ICLR2023[31]	71.0	40.8	58.2	56.8	56.5	68.2	40.0	55.4	53.7	54.3	66.4	38.0	47.3	47.2	49.7	53.4	-3.3
VDP	AAAI2023[8]	70.5	41.1	62.1	59.5	58.3	70.4	41.1	62.2	59.4	58.2	70.4	41.0	62.2	59.4	58.2	58.2	+1.5
DAT	**ours**	**71.7**	**44.4**	**65.4**	**62.9**	**61.1**	**71.6**	**45.2**	**63.7**	**63.3**	**61.0**	**70.6**	**44.2**	**63.0**	**62.8**	**60.2**	**60.8**	**+4.1**



PERFORMANCE COMPARISON FOR SHIFT DATASET'S CONTINUOUS VALIDATION SET. ACC DENOTES THE AVERAGE ACCURACY SCORE.

Scenarios	*Daytime – Night*		*Clear – Foggy*		*Clear – Rainy*		Mean
Method	mIoU	ACC	mIoU	ACC	mIoU	ACC	mIoU
Source	64.22	71.84	61.51	69.87	66.14	73.87	64.01
TENT	64.21	71.67	61.65	69.76	66.11	73.68	63.99
CoTTA	68.06	74.18	64.78	71.41	69.92	76.29	67.61
Ours	**68.63**	**75.34**	**65.31**	**72.68**	**70.56**	**77.34**	**68.17**

ABLATION: CONTRIBUTION OF EACH COMPONENT.

	TS	DSP	TRP	mIoU↑	Gain
Ex_1				56.7	/
Ex_2	✓			58.7	+2.0
Ex_3	✓	✓		60.2	+3.5
Ex_4	✓		✓	60.3	+3.6
Ex_5	✓	✓	✓	61.1	+4.4

EFFECT OF SELECT PARAMETERS' SELECTION METHOD. W/O PAU MEANS THE SELECTION OF 10% PARAMETERS FROM THE FIRST FRAME IN THE TARGET SEQUENCE. W PAU DENOTES THE UTILIZATION OF OUR PAU METHOD TO SELECT AROUND 10% PARAMETERS.

	w/o PAU		w PAU	
Method	mIoU	ACC	mIoU	ACC
Confidence	59.1	71.1	60.6	71.3
Uncertainty	60.3	71.4	61.1	72.2

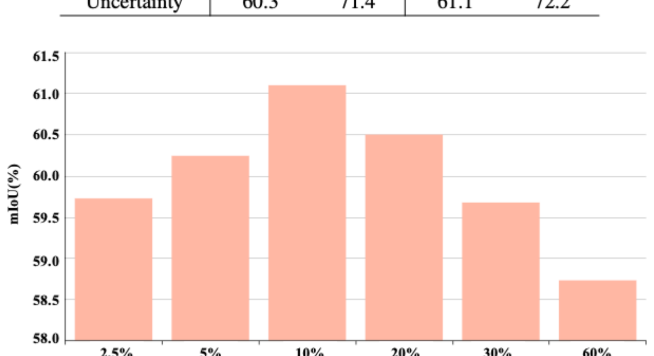


Fig. 4. Different percentages of updated parameters (DSP + TRP)

Conclusion

Our Distribution-Aware Tuning (DAT) method presents an efficient and practical solution for Semantic Segmentation Continual Test-Time Adaptation (CTTA) in real-world scenarios. DAT intelligently selects and fine-tunes two distinct sets of trainable parameters: domain-specific parameters (DSP) and task-relevant parameters (TRP). This helps mitigate issues of error accumulation and catastrophic forgetting during the continual adaptation process.

Given that CTTA in the context of autonomous driving operates on temporal sequences, we introduce a Parameter Accumulation Update (PAU) strategy. This strategy enhances the stability of parameter selection and updates, ensuring a more reliable adaptation process.

Reference

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