Great Ape Detection with Self-reinforcing Loops Using Dynamic Curriculum Learning

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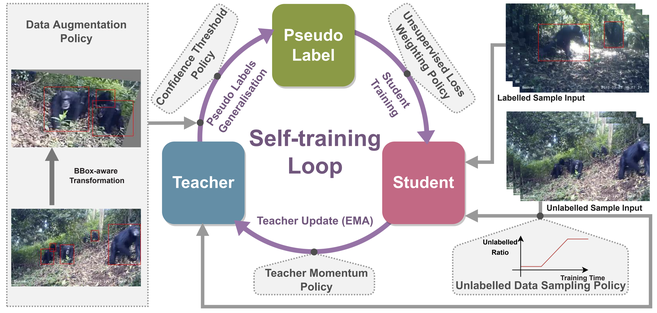
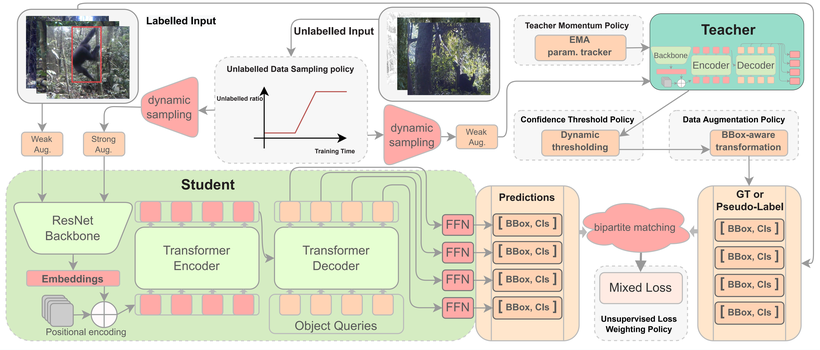
Introduction

Animals in the natural habitats are often hard to detect because of the challenging environment. Previous methods often relies on large dataset pre-training and then fine-tuning on the specific dataset. But for animal detection from the camera trap, it lacks large-scale labelled dataset, however, there are thousands of unlabelled video footage filmed in the natural habitats. Inspired by this, we designed a semi-supervised detection algorithm that can leverage the large-scale unlabelled data for assisting the animal detection.

Conceptual Overview and Detection Pipeline





Ablation Study

(a)

Sample Policy π	mAP
Linear Increase	61.62
Linear Increase$^{\dagger *}$	**64.73**
Linear Decrease	53.47
Linear Decrease†	59.99
Constant	60.46

(b)

Loss Weight Policy α	mAP
Constant 0.1	62.18
Constant 0.5	63.98
Constant 2.0	54.68
Linear $0.1 \rightarrow 1^{*}$	**64.73**
Linear $0.1 \rightarrow 2$	61.17

(c)

Conf. Threshold Policy ς	mAP
Constant 0.05	51.73
Constant 0.9	58.61
Linear $0.1 \rightarrow 0.6$	64.10
arctan $0.1 \rightarrow 0.6^{*}$	**64.73**

(f)

Initialisation	mAP
Random Init.	0.17
SWAV Init.*	**64.73**
supervised Init.	61.55

(d)

Augmentation Policy $\mathcal{A}$	mAP
No Augmentation	55.41
Augmentation with $\mathcal{A}_w$, $\mathcal{A}_s^*$	**64.73**

(e)

Momentum Policy m	mAP
Constant 0.999	60.07
cos $0.998 \rightarrow 0.9998^{*}$	**64.73**

Bipolar Behavioural self-training loops

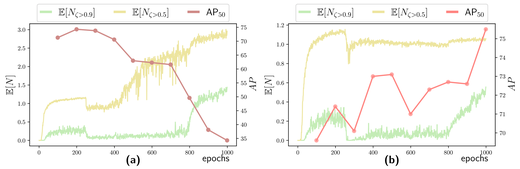


Figure 1: Bipolar Behavioural Dynamic of Learning

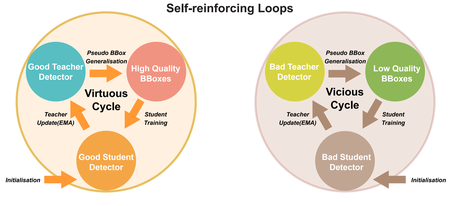
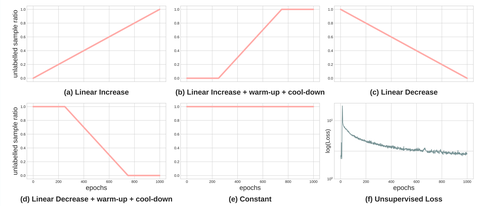


Figure 2: Process within Self-reinforcing Loops

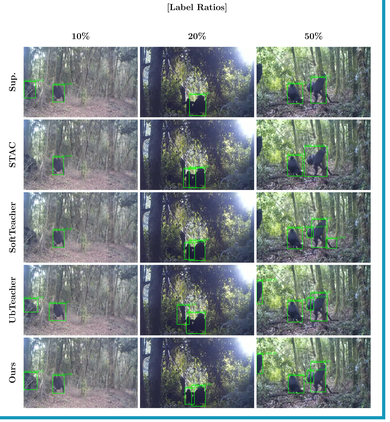
Unlabelled Data Sampling Policy



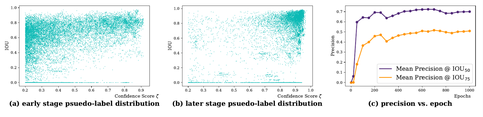
- Best policy achieved when unlabelled loss and unlabelled ratio are negatively correlated
- Gradually increase unlabelled input *i.e.* curriculum learning

Results on PanAfrican

Method	Labelled Ratio	Setting	mAP	mAP$_{50}$	mAP$_{75}$
Supervised baseline	10%	PLD	32.17 ± 0.70	75.57 ± 1.24	21.40 ± 2.45
STAC	10%	PLD	38.04 ± 3.88	73.31 ± 7.01	35.34 ± 2.31
SoftTeacher*	10%	PLD	39.37 ± 7.97	63.03 ± 11.42	44.50 ± 9.72
Ubteacher*	10%	PLD	44.03 ± 0.26	76.69 ± 2.15	47.25 ± 1.21
Ours	10%	PLD	$\mathbf{45.96} \pm 2.97$	$\mathbf{78.10} \pm 6.14$	$\mathbf{47.67} \pm 3.12$
Supervised baseline	20%	PLD	46.93 ± 1.30	86.47 ± 0.74	46.00 ± 2.42
STAC	20%	PLD	51.35 ± 2.39	83.71 ± 2.24	56.58 ± 4.12
SoftTeacher*	20%	PLD	50.87 ± 2.99	79.57 ± 6.29	58.67 ± 2.89
UbTeacher*	20%	PLD	55.78 ± 0.45	88.07 ± 1.88	63.02 ± 0.67
Ours	20%	PLD	$\mathbf{59.01} \pm 1.57$	$\mathbf{89.23} \pm 0.98$	$\mathbf{66.95} \pm 2.45$
Supervised baseline	50%	PLD	59.50 ± 1.40	92.37 ± 0.92	65.47 ± 2.04
STAC	50%	PLD	59.93 ± 1.21	92.35 ± 0.65	67.40 ± 2.10
SoftTeacher*	50%	PLD	60.47 ± 3.58	86.93 ± 4.23	69.63 ± 3.35
UbTeacher*	50%	PLD	61.66 ± 1.73	91.79 ± 1.45	$\mathbf{72.71} \pm 1.42$
Ours	50%	PLD	$\mathbf{63.39} \pm 1.34$	$\mathbf{92.96} \pm 0.68$	70.00 ± 3.45
Supervised baseline	100%	FLD	65.53	95.28	74.52
STAC	100%	FLD	46.98	80.76	50.61
SoftTeacher*	100%	FLD	**70.70**	94.90	**81.90**
UbTeacher*	100%	FLD	66.45	94.13	79.35
Ours	100%	FLD	67.64	**95.87**	76.81

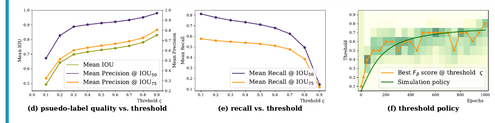


Unsupervised weighting policy



- Unreliable pseudo-labels in early stage as shown Fig. (a)
- More reliable pseudo-labels in later stage in Fig. (b)
- Precision of pseudo-labels increase in Figure (c)
- Dynamic weighting to compensates unreliable pseudo-labels
- $\mathcal{L}_{all}(\theta) = \mathcal{L} + \alpha\mathcal{L}'$
- Dynamic weighting α for unsupervised loss .

Confidence Threshold Policy



- Pseudo-label quality increase along with threshold in Fig. (d)
- Recall of pseudo-label decrease along with threshold in Fig. (e)
- Use F_β to balance False Negatives *vs* False Positives
- Fig. (f) shows the F_β score for threshold at each epoch.
- Orange curve is the best choice of threshold for each epoch.
- the green curve is our simulation policy

Other Policies

Data Augmentation Policy

- Ensuers consistent augmentation of unlabelled data
- Contains geometric transformation and colour transformation
- applies week and strong augmentation

Teacher Momentum Policy

- Controls the update spped of teacher model
- Pseudo-label precision increase steeply in the early training stages, slowly in the later training stages
- Consine increae of momentum coeeffecient

Results on COCO

Method	Venue	1% PLD	5% PLD	10% PLD
STAC [1]	Arxiv 2020	13.97	24.38	28.64
Instant-Teaching [6]	CVPR 2021	18.05	26.75	30.40
Humble Teacher [4]	CVPR 2021	16.96	27.70	31.61
UbTeacher [5]	ICLR 2021	20.75	28.27	31.50
SoftTeacher [3]	ICCV 2021	20.46	**30.74**	34.04
MUM [7]	CVPR 2022	**21.88**	28.52	31.87
Ours	-	17.34	29.75	**34.45**

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