Progressive Exploration-Conformal Learning for Sparsely Annotated Object Detection in Aerial Images

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Motivations:

Recently, object detection has gained widespread attention, but the demand for a large amount of labeled data is time-consuming and labor-intensive.

SSOD methods focus on general images, and cannot consider the unique characteristics of objects in aerial images, such as dense arrangements, rich contextual relationships, and large complex scenes.

For example, the average objects per image are 68.4 vs 7.7 in DOTA and COCO datasets, respectively.

Therefore, we address the sparsely annotated object detection (SAOD) task in aerial images.

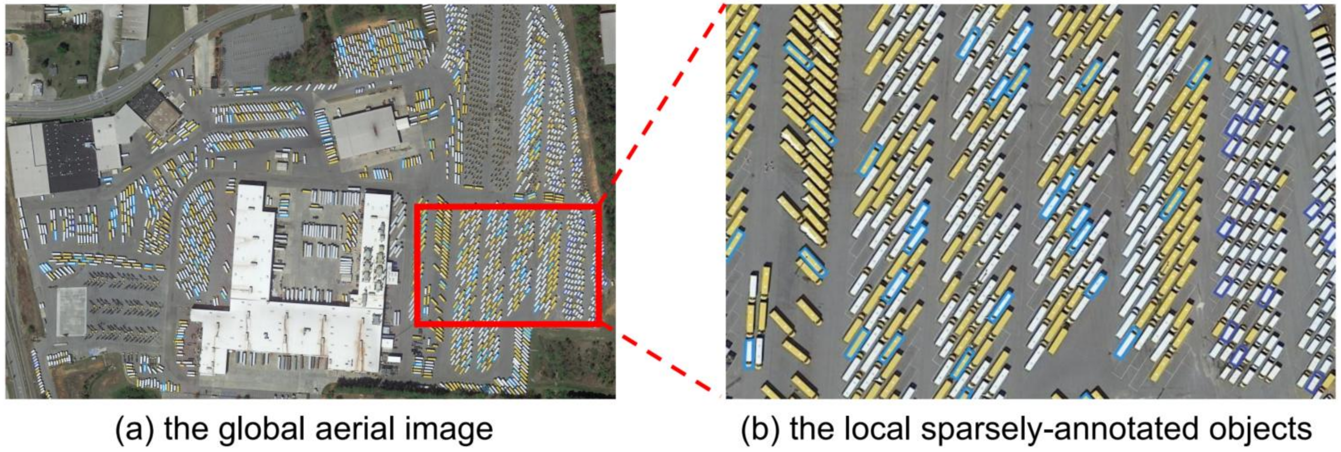
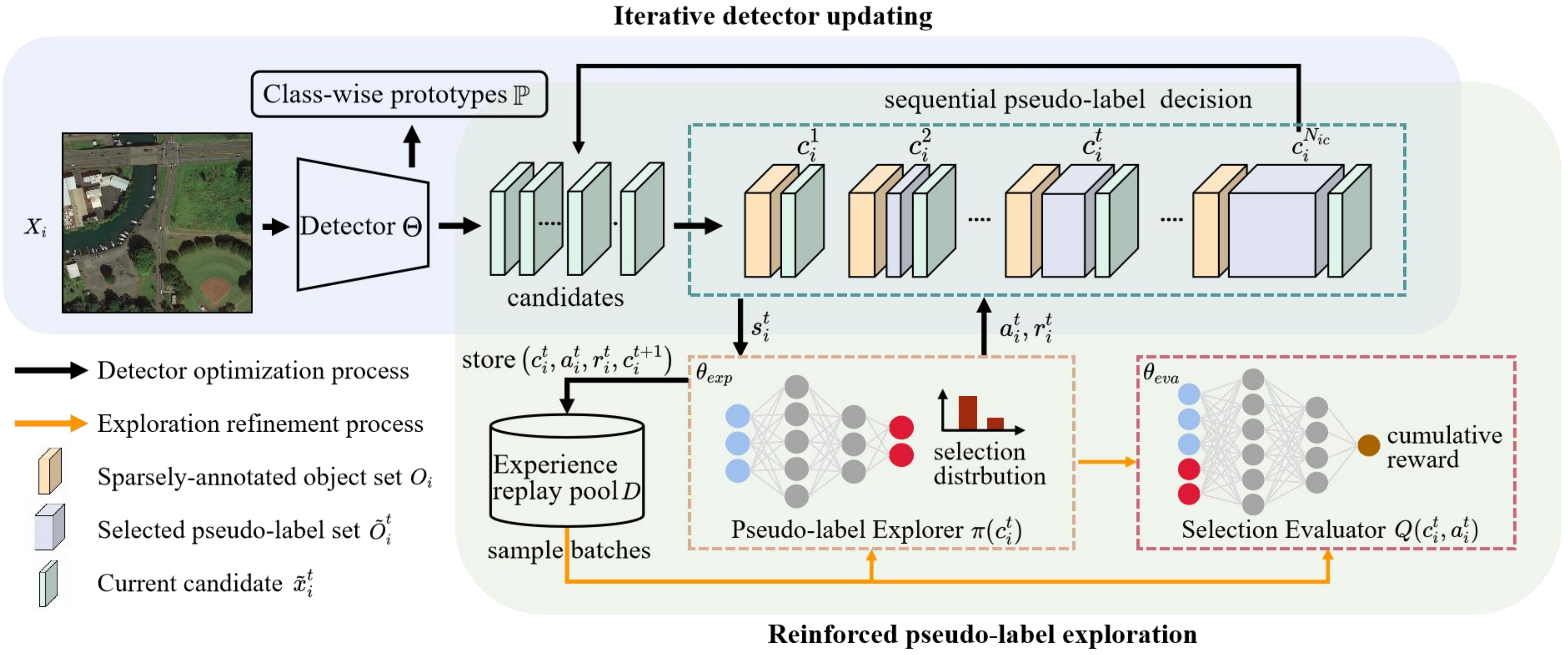


Figure 1: An example of sparsely annotated objects in an aerial image. Here a small part of objects are annotated, e.g., large vehicles with the light blue, and small vehicles with the dark blue.

Overview:

We integrate detector updating and reinforced pseudo-label exploration into a closed-loop framework.
In the exploration refinement process, we introduce pseudo-label explorer π and selection evaluator Q to continuously optimize pseudo-label exploration policy based on the accumulated experience D.
During the optimization of the detector Θ, we simultaneously perform the sequential pseudo-label decision on the candidates, inferred by the optimized detector.



Details:

Conformal Pseudo-label Explorer is to learn an adaptive pseudo-label exploration policy to determine whether to select the current candidate.

Multi-clue Selection Evaluator is to assess the current exploratory characteristic and selection policy, providing instructive feedback for policy optimization.

- The instant exploratory reward is as follows:

$$r_i^t = \begin{cases} +1, a_i^t = 1, \psi(\tilde{x}_i^t) \leq 0 | a_i^t = 0, \psi(\tilde{x}_i^t) \geq 0 \\ -1, a_i^t = 1, \psi(\tilde{x}_i^t) > 0 | a_i^t = 0, \psi(\tilde{x}_i^t) < 0 \end{cases}$$

- The reward function considers information entropy and confidence margin:

$$\psi(\tilde{x}_i^t) = \Delta H(\tilde{x}_i^t) + \xi \Delta U(\tilde{x}_i^t)$$

- The target value can be defined as:

$$V_i^t = r_i^t + \gamma Q(c_i^{t+1}, a_i^{t+1})$$

- The function to update explorer and evaluator:

$$\mathcal{L}_{ref} = \underbrace{(V_i^t - Q(c_i^t, a_i^t))^2}_{\text{Appro. target value}} - \underbrace{Q(c_i^t, a_i^t)}_{\text{Max. cum. reward}}$$

- The ultimate goal of our PECL:

$$\mathcal{L}_{det} = \sum_i^N \left(\frac{1}{|O_i|} \sum_{j=1}^{|O_i|} (\mathcal{L}_{cls}(x_i^j, y_i^j) + \mathcal{L}_{reg}(x_i^j, b_i^j) + \mathcal{L}_{pot}(x_i^j, \mathbb{P})\right)) + \sum_i^N \left(\frac{1}{|\tilde{O}_i^{N_{ic}}|} \sum_{u=1}^{|\tilde{O}_i^{N_{ic}}|} (\mathcal{L}_{cls}(\tilde{x}_i^u, \tilde{y}_i^u) + \mathcal{L}_{reg}(\tilde{x}_i^u, \tilde{b}_i^u)\right))$$

Experiments & Results

Performance comparisons of different detector baselines for the OBB task on the DOTA dataset at different label rates.

	Method	PL	BD	BR	GTF	SV	LV	SH	TC	BC	ST	SBF	RA	HA	SP	HC	mAP(%)
1%	S^2A-Net	57.27	50.85	20.13	59.11	36.98	32.58	37.97	83.75	49.15	27.89	42.48	48.70	18.33	24.54	12.35	40.14
	S^2A-Net w/ PECL	73.30	63.17	25.57	62.35	55.87	48.41	59.71	90.00	66.99	53.07	37.35	50.43	27.13	38.45	12.18	**50.39**
	OR-CNN	69.05	69.69	23.81	62.53	40.11	37.65	38.22	88.14	67.52	46.01	51.83	60.68	28.80	36.97	19.39	49.36
	OR-CNN w/ PECL	79.57	74.21	32.73	63.70	50.93	48.04	48.22	90.15	77.78	56.75	55.75	59.50	41.62	48.11	26.51	**56.91**
	ReDet	60.36	62.98	26.16	66.08	34.24	39.99	29.35	87.42	68.58	50.11	49.94	56.59	30.75	40.43	18.51	48.10
	ReDet w/ PECL	86.09	72.16	38.91	65.05	67.29	72.01	75.40	89.17	78.52	70.42	56.75	57.68	54.09	53.50	18.72	**63.72**
2%	S^2A-Net	56.92	48.39	21.41	61.37	42.76	35.06	46.46	85.02	54.32	35.45	38.11	50.41	20.56	29.15	3.35	41.92
	S^2A-Net w/ PECL	74.57	58.63	26.14	62.36	60.68	55.81	69.71	89.64	65.52	62.58	36.53	52.20	31.45	42.58	18.71	**53.81**
	OR-CNN	68.78	71.00	24.81	63.66	47.06	37.65	45.59	87.38	70.69	51.26	53.54	57.26	28.20	44.52	23.40	51.65
	OR-CNN w/ PECL	79.80	72.87	31.12	67.52	58.97	51.18	66.16	90.15	74.48	58.96	53.41	60.98	42.97	44.95	26.43	**58.66**
	ReDet	59.73	64.67	23.65	72.47	40.07	40.37	53.99	87.90	64.66	48.02	51.16	57.63	33.20	46.65	23.79	51.20
	ReDet w/ PECL	87.27	73.30	41.54	70.35	67.19	71.88	81.14	89.08	73.33	77.97	55.47	61.82	60.77	55.55	32.09	**66.58**
5%	S^2A-Net	65.85	49.72	21.97	59.97	56.63	52.17	66.53	87.14	57.84	48.72	38.07	50.47	20.78	36.08	19.75	48.78
	S^2A-Net w/ PECL	78.18	63.18	30.36	63.85	66.22	64.50	73.06	90.26	69.54	64.57	41.92	50.56	32.99	43.54	28.56	**57.42**
	OR-CNN	78.13	71.05	24.62	64.69	57.81	57.64	70.99	88.62	67.80	53.27	49.46	60.68	30.71	37.51	31.46	56.30
	OR-CNN w/ PECL	86.95	73.10	30.17	67.68	68.34	69.61	80.10	90.07	74.91	71.95	47.80	59.82	48.26	52.43	40.06	**64.08**
	ReDet	78.21	68.73	31.49	69.65	54.25	57.11	63.27	88.38	62.21	49.87	52.09	56.34	41.12	44.69	23.52	56.06
	ReDet w/ PECL	88.38	71.19	36.56	64.78	72.50	71.38	82.51	89.65	75.85	76.66	50.79	60.95	61.53	61.00	42.08	**67.06**
10%	S^2A-Net	73.92	57.80	28.38	62.52	63.08	64.10	71.33	88.10	59.29	60.02	42.47	52.71	33.22	44.55	14.21	54.39
	S^2A-Net w/ PECL	80.40	75.51	38.31	65.62	65.93	70.60	69.21	88.97	78.77	69.69	53.13	56.31	52.84	53.29	18.71	**62.49**
	OR-CNN	77.51	69.97	33.06	63.23	68.25	69.09	75.27	88.36	65.87	63.19	52.26	65.89	42.29	45.69	51.72	62.11
	OR-CNN w/ PECL	87.07	75.11	37.59	65.78	69.88	72.53	82.44	90.47	77.33	75.82	53.24	65.07	54.58	59.12	50.11	**67.74**
	ReDet	78.75	70.17	32.21	69.76	59.90	67.18	73.86	87.06	66.62	58.84	53.44	56.45	50.91	43.70	35.89	60.32
	ReDet w/ PECL	87.23	75.15	42.24	67.21	74.05	73.95	85.42	90.41	84.47	71.95	59.35	57.83	64.48	61.36	45.30	**69.36**

Comparison with state-of-the-art methods on the DOTA dataset at the 5% label rate.

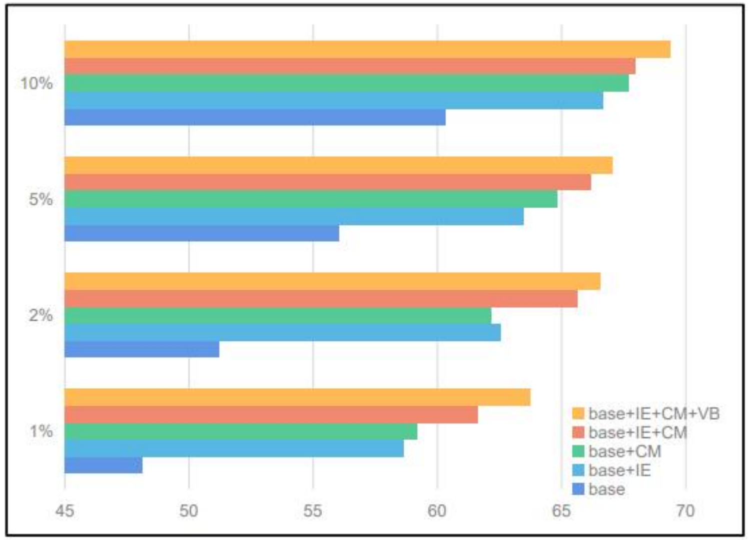
Setting	Method	mAP(%)
Supervised	S^2A-Net†	48.78
	ReDet*	56.06
Semi-supervised	SOOD†	53.74
	Unbiased Teacher*	64.74
Sparse-annotated	Calibrated Teacher†	55.81
	S^2A-Net† w/PECL	**57.42**
	BRL*	65.04
	Co-mining*	65.35
	Region-based*	65.71
	ReDet* w/PECL	**67.06**

Performance comparisons of different strategies when selecting pseudo-labels at the 1% label rate.

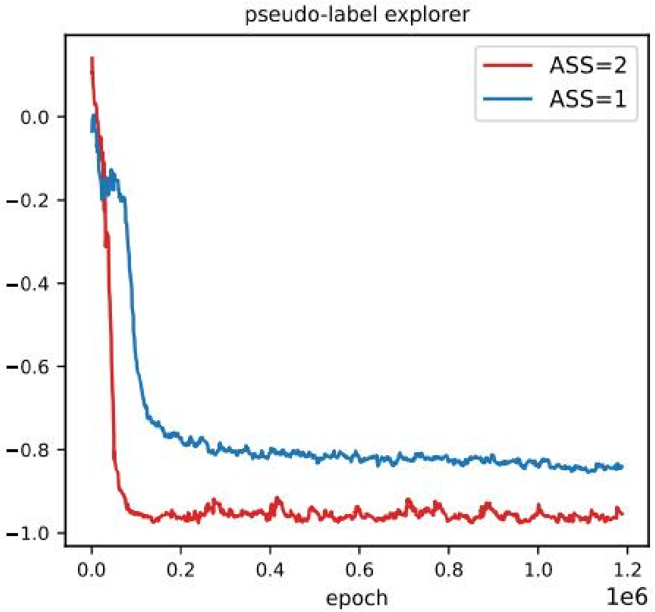
Setting	Pseudo-label explorer	Selection evaluator	Experience replay mechanism	mAP(%)
I	-	-	-	48.10
II	✓	-	-	60.84
III	✓	✓	-	61.31
IV	✓	✓	✓	**63.72**

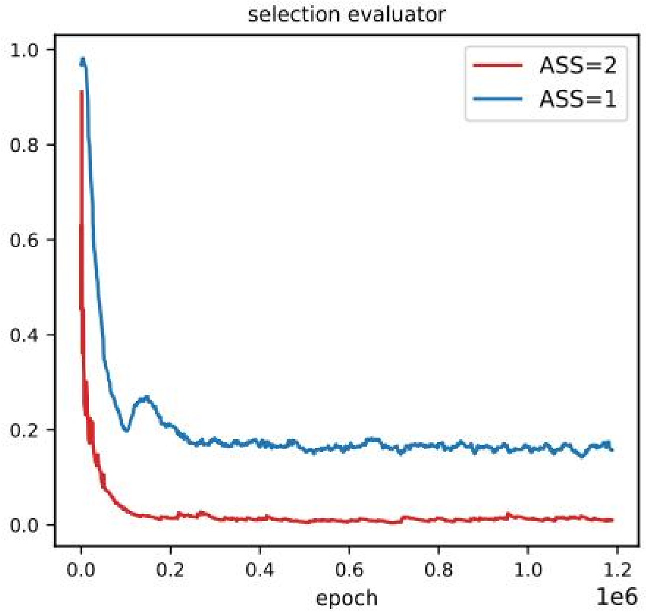
Experiments & Results

Performance comparisons of different reward settings at various label rates.



Loss curves of conformal pseudo-label explorer and multi-clue selection evaluator under different action spaces at the 1% label rate.





Conclusion

- We propose a progressive exploration conformable learning framework that integrates the detector updating and the conformal pseudo-label exploration into an iteratively co-enhancing system.
- We perform the pseudo-label exploration to mine more high-quality pseudo-labels by considering contextual information in large complex scenes, consisting of two modules: the conformal pseudo-label explorer and multi-clue selection evaluator.

Limitation

- The current framework is specifically designed for scenes with densely distributed objects, which may not perform optimally in general scenes with less dense object arrangements.
- The incorporation of reinforcement learning algorithms results in increased overall training time compared to traditional methods.

Thanks for listening!