SAROD: EFFICIENT END-TO-END OBJECT DETECTION ON SAR IMAGES WITH REINFORCEMENT LEARNING

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Introduction: Object Detection on Satellite images

- Natural Images


Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." European conference on computer vision. Springer, Cham, 2014.

- Satellite Images



Xia, Gui-Song, et al. "DOTA: A large-scale dataset for object detection in aerial images." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.

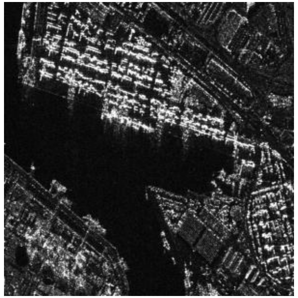
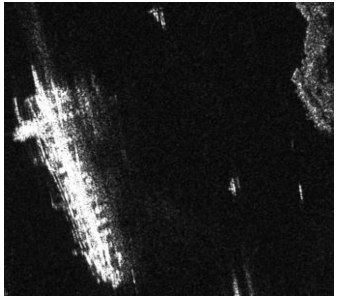
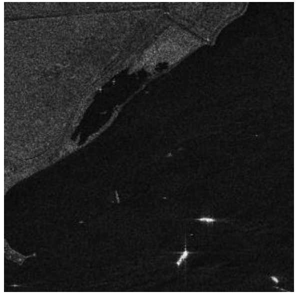
Introduction: Object Detection on SAR images

- Electro-Optical (EO) Satellite Images



https://ksatdb.kari.re.kr
https://eol.jsc.nasa.gov

- Synthetic Aperture Radar (SAR) Satellite Images

Wei, Shunjun, et al. "HRSID: A high-resolution SAR images dataset for ship detection and instance segmentation." Ieee Access 8 (2020): 120234-120254.

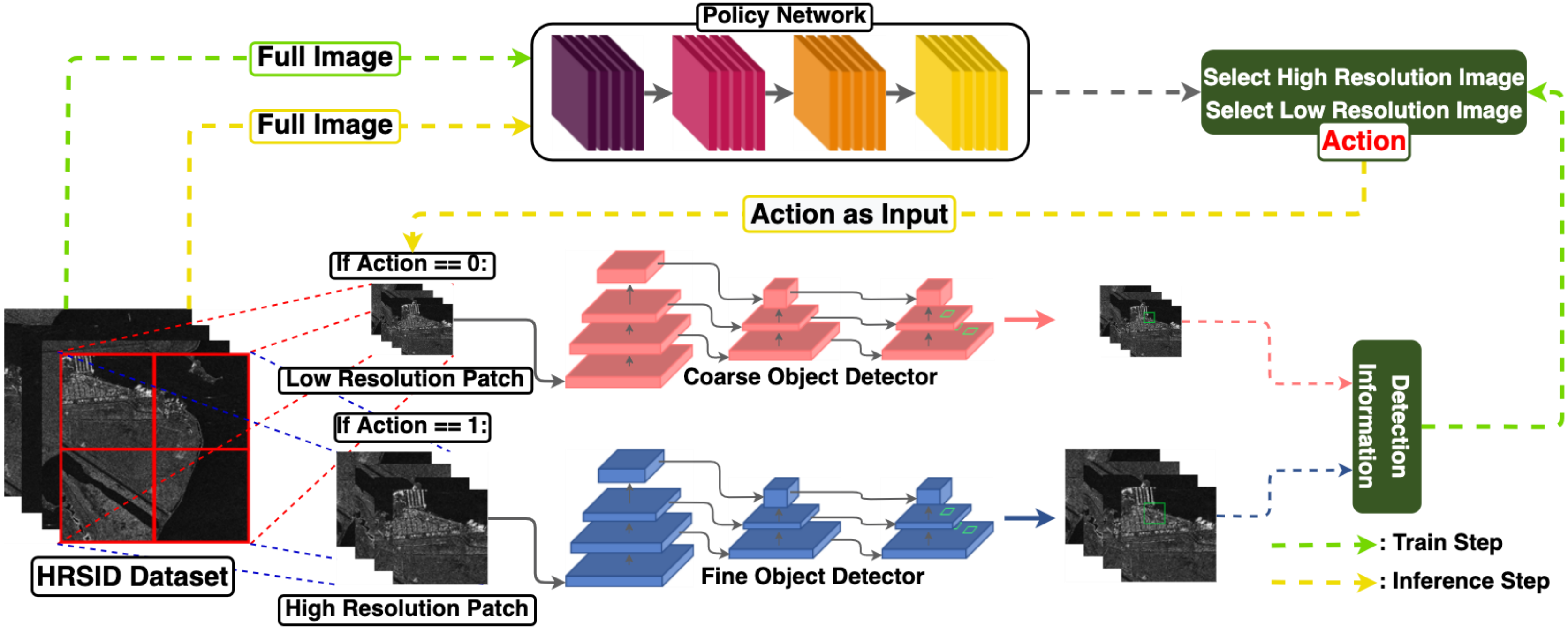
Our Motivations

- Using SAR images which have gained much attention recently due to their persistency and endurability in challenging weather conditions.

- Minimizing High-Resolution (HR) data usage for efficiency, while maintaining high accuracy.

- Applying an end-to-end framework so that pre-trained detection models are not required.

Our Proposal Architecture: SAROD



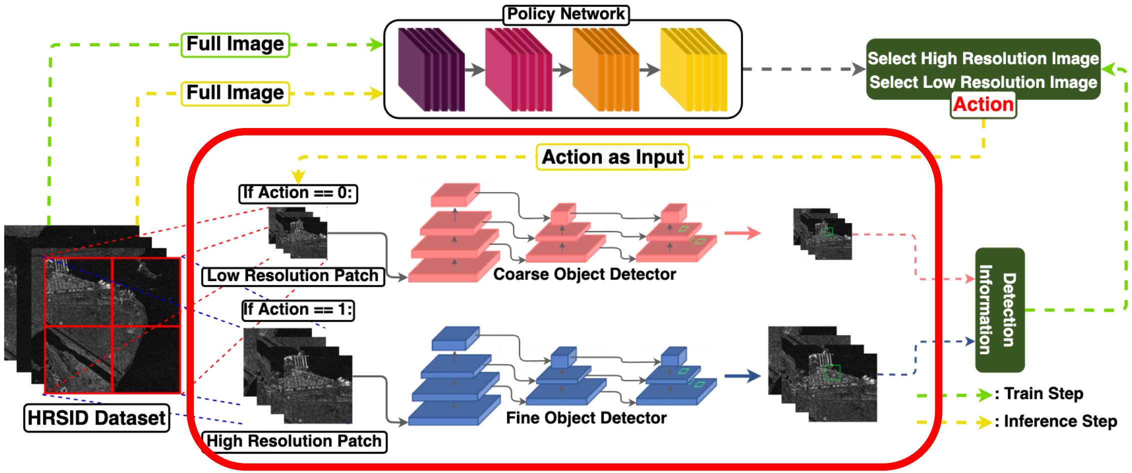
<Architecture Overview>

Proposed Approach

Object Detectors

- Fine and Coarse-grained object detectors

We employ both fine-grained object detector and light coarse-grained object detector based on input size (e.g., High-Resolution (480) vs. Low-Resolution (96) pixels)



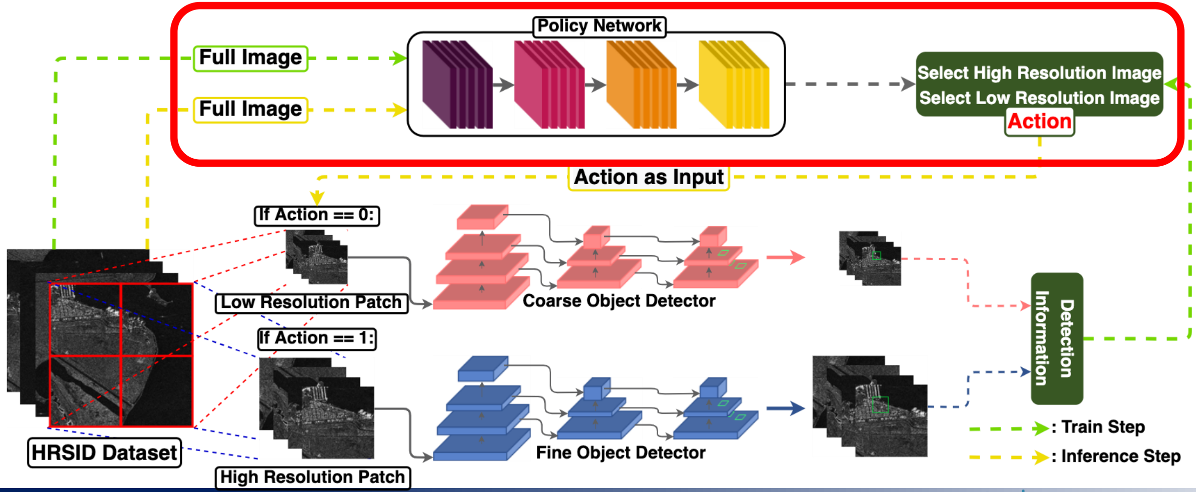
Proposed Approach

Policy Agent

- ResNet-based Policy network

1) Determines the efficient image patches

2) Performs binary classification in each patch (High resolution vs. Low-resolution)



Reward Function Design

1. Difference of precision reward (R_{diff})

- Favors policies that choose the LR patches, only if the precision is maintained.
- Otherwise, minimize the HR patches.

$$R_{diff} = \sum_{n=1}^{m} a \cdot (P_f - P_c) - (1 - a) \cdot (P_f - P_c)$$

$$P_f = Prec(\hat{y}_f^n, Y^n),\ P_c = Prec(\hat{y}_c^n, Y^n) + \beta.$$

Reward Function Design

2. Acquisition cost reward (R_{aqcost})

  ○ Provides more rewards for the action choosing the LR patches

$$R_{aqcost} = (m - \sum_{n=1}^{m} a_c^n)/m),$$

3. Objectness reward (R_{obj})

  ○ Penalizes, if HR patches are chosen when there is no object

$$R_{obj} = \sum_{n=1}^{m} \|s_i - Y_n^{obj}\|_1^1,$$

Reward Function Design

- Final reward function

Based on these three reward terms, we calculate the final reward function R.

$$R = R_{diff} + \lambda_{aqcost} R_{aqcost} + \lambda_{obj} R_{obj},$$

Proposed Approach

RL Agent Training

- REINFORCE algorithm + Advantage function

The advantage function as a Temporal Difference (TD), which reduces the variance

$$\nabla_{\theta_{rl}} J = \mathbb{E}\Big[A \sum_{n=1}^{m} \nabla_{\theta_{rl}} \log(s^n a^n + (1 - s^n)(1 - a^n))\Big],$$

$$A = R(a, Y) - R(\hat{a}, Y),$$

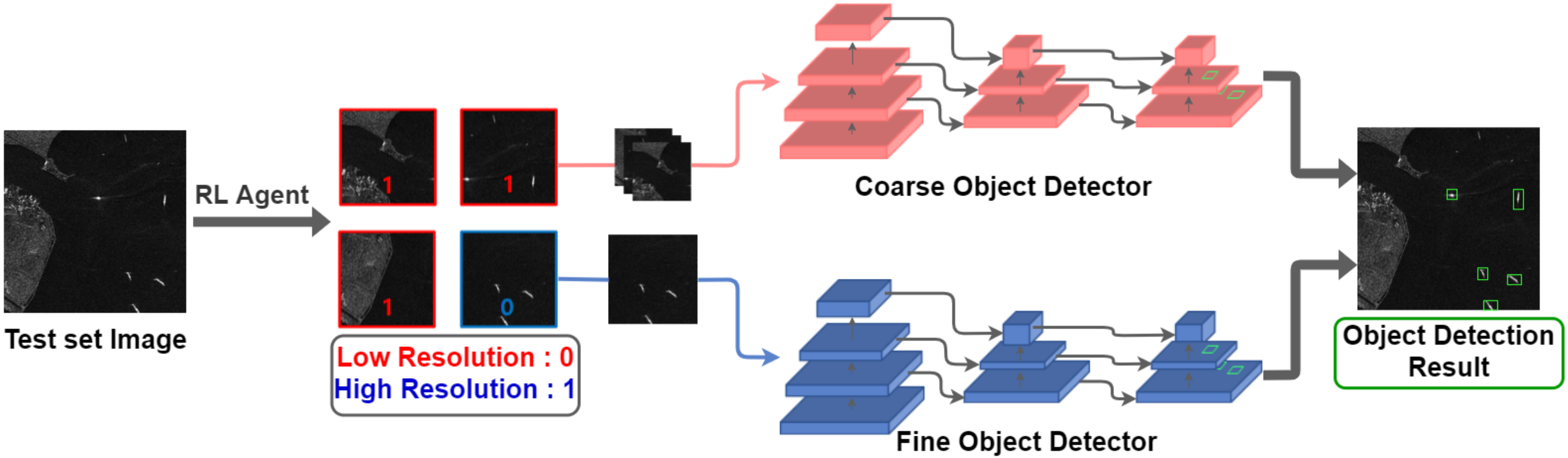
- With clipping function → decay

$$s = \alpha s + (1 - \alpha)(1 - s),$$

$$\alpha = clip(\alpha + epoch * 0.001,\ 0.6,\ 0.95),$$

Proposed Approach

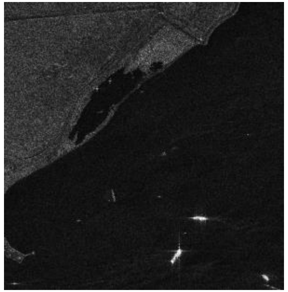
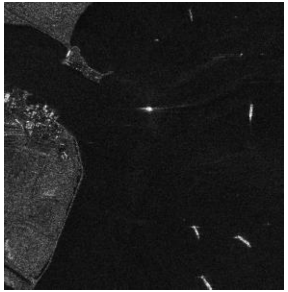
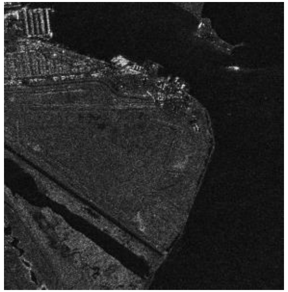
- Inference Stage



Training details

Dataset description

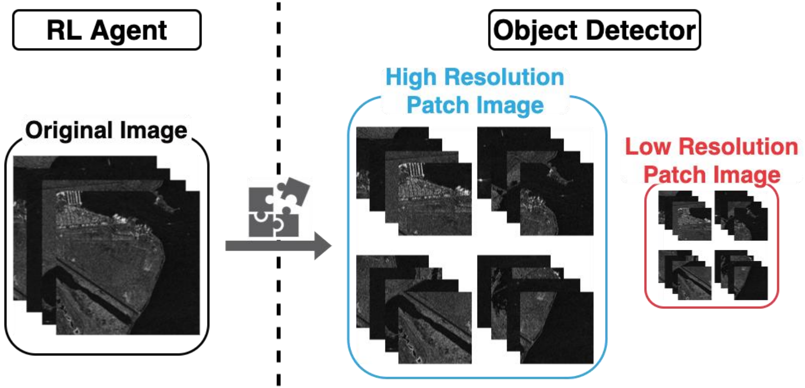
- High Resolution SAR Images Dataset (HRSID)
    - 16,951 ships on 5,604 images, cropped 800×800 pixel size
    - 65% train and 35% test sets

Training details

Dataset description

- Dataset Preprocessing
  - HRSID dataset image resized to create low-resolution image patches
  - Overlapping size=80, l_fine =480 for high resolution patch image, and l_coarse=96 for low resolution patch image



Experimental Results

mAP and HR ratio Performance on HRSID Dataset

Method	Resolution	mAP (%)	HR Ratio
Faster R-CNN (ResNet-50)	480	80.1	1
RetinaNet	480	66.6	1
YOLOv3	480	78.1	1
YOLOv5	480	**84.4**	1
HRSDNet	1,000	89.3	1
EfficientOD (YOLOv5)	HR:480 / LR:96	75.3	0.98
Ours (YOLOv5)	HR:480 / LR:96	**83.2**	**0.89**

Ablation Study

Need for Objectness reward (r) & Advantage function (a)

Method	Resolution	mAP (%)	HR Ratio
YOLOv5 (fine)	480	84.4	1
YOLOv5 (coarse)	96	53.5	0
Ours (without r, a)	HR:480 / LR:96	**74.5**	0.73
Ours (without r)	HR:480 / LR:96	84.4	**1**
Ours	HR:480 / LR:96	**83.2**	**0.89**

Ablation Study

Effect of larger image sizes and runtime performance

Method	Resolution	Runtime (ms)	HR Ratio
YOLOv5 (fine)	4,800	**956.7**	1
YOLOv5 (coarse)	960	235.4	0
Ours	HR:4,800 / LR:960	**885.5**	**0.89**

Contribution

1. We apply RL for object detection in SAR images, achieving high performance and improving efficiency.

2. We propose a novel framework SAROD proposing the entire training and inference process into the single end-to-end learning pipeline.

3. We develop the new reward function for robust training of policy network to achieve the optimal decision by carefully selecting the LR vs. HR images.

4. We demonstrate the effectiveness of SAROD with extensive experiments.

Thank you!

https://dash-lab.github.io/
https://airsc.ai/

Code is available here:

https://github.com/JunHyungKang/SAROD_ICIP