Article

SAR-to-Infrared Domain Adaptation for Maritime Surveillance with Limited Data

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Abstract: Deep Learning (DL) algorithms need extensive amounts of data for classification tasks, which can be costly in specialized fields like maritime monitoring. To address data scarcity, we propose a fine-tuning approach leveraging complementary Infrared (IR) and Synthetic Aperture Radar (SAR) datasets. We evaluated our method using the ISDD, HRSID, and FuSAR datasets, employing VGG16 as a shared backbone integrated with Faster R-CNN (for ship detection) and a three-layer classifier (for ship classification). Results showed significant improvements in IR ship detection (mAP: +20%, Recall: +17%) and modest but consistent gains in SAR ship tasks (F1-score: +3%, Recall: +1%, mAP: +1%). Our findings highlight the effectiveness of domain adaptation in improving DL performance under limited data conditions.

Keywords: domain adaptation; Ship classification; remote sensing; infrared; SAR

1. Introduction

Effective maritime surveillance aids environmental sustainability by preventing illegal fishing, pollution, and illegal trafficking. Maritime traffic monitoring is particularly challenging due to vast oceanic coverage, with maritime transport responsible for approximately 80% of the world's trade [1]. To efficiently monitor such extensive areas, satellite-based surveillance using Synthetic Aperture Radar (SAR) and Infrared (IR) imaging has proven effective.

Classical Machine Learning techniques, when applied to satellite imagery, require extensive manual effort for feature extraction, consuming significant time and resources. Deep Learning (DL) algorithms offer a substantial advantage by automatically identifying and extracting useful features directly from data, significantly reducing manual intervention and improving task-specific outcomes such as classification, detection, and segmentation.

However, DL algorithms typically require large datasets to iteratively learn and effectively identify discriminative features. In maritime surveillance, acquiring substantial amounts of SAR and IR data is costly, limiting the potential performance of DL methods. Several researchers have employed DL for maritime tasks, such as ship detection [2–4] and ship classification [5–7], highlighting both the potential and current limitations due to data scarcity.

To address data limitations, techniques such as data augmentation, transfer learning, and domain adaptation have been proposed. In this study, we specifically propose a domain adaptation approach using complementary SAR and IR datasets to improve the effectiveness of DL models in maritime traffic monitoring. The main contributions of this work are:

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1. Improved IR detection performance, achieving more than a 17% increase in Recall and Mean Average Precision (mAP).
2. Enhanced SAR classification performance, achieving a 3% increase in the F1-score compared to the baseline.

In the following sections, we briefly discuss the relevant background, outline our methodology, present and analyze our experimental results, and conclude the study.

2. Methodology

Our methodology comprises two main stages: pretraining and fine-tuning. The complete workflow is illustrated in Figure 1.

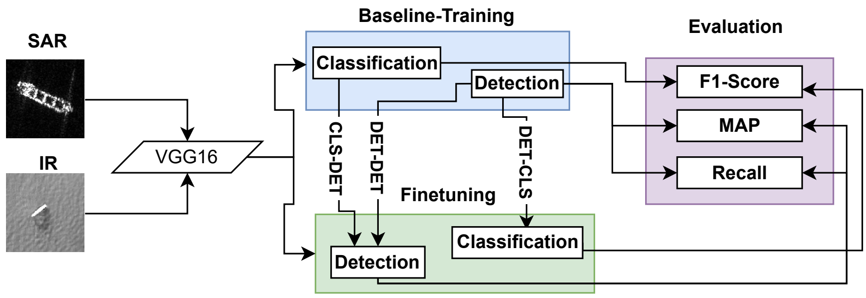

Figure 1. Experimental setup illustrating a shared VGG16 backbone for SAR and IR feature extraction. Models are baseline-trained and fine-tuned using CLS-DET, DET-DET, and DET-CLS pipelines, evaluated by F1-score (classification), mAP, and Recall (detection).

2.1. Training Pipelines and Models

We explored three distinct fine-tuning pipelines:

1. Detection-to-Detection (DET-DET): A shared Faster R-CNN with a VGG16 backbone is initially trained on SAR detection data and subsequently fine-tuned on IR detection data, and vice versa.
2. Classification-to-Detection (CLS-DET): A VGG16-based classifier is first trained on SAR classification data. Its trained backbone is then integrated into Faster R-CNN and fine-tuned for IR detection tasks.
3. Detection-to-Classification (DET-CLS): The Faster R-CNN model with a VGG16 backbone is initially trained on IR detection data. The backbone is then extracted and fine-tuned for SAR classification tasks using a three-layer classifier.

2.2. Datasets

We utilized three publicly available datasets for our experiments:

1. FuSAR-Ship [8]: A high-resolution SAR ship classification dataset comprising 15 main classes and 98 subclasses, with image dimensions of 512×512. For our experiments, we selected four primary classes: Bulk, Cargo, Tanker, and Fishing.
2. HRSID [9]: A high-resolution SAR ship detection dataset containing 16,951 images, each with a resolution of 800×800.
3. ISDD [10]: An IR ship detection dataset containing 3,061 ship instances, with images sized 500×500.

2.3. Evaluation and Training Parameters

Classification performance was evaluated using the F1-score, while detection performance was measured by mAP and Recall. All models were trained with a batch size of 32, a learning rate of 1×10^{-4}, and optimized using the Adam optimizer.

3. Results

We evaluated our method across two experimental setups: (1) Same-task (Detection-to-Detection), and (2) Cross-task (Classification-to-Detection and vice versa).

3.1. Same-task Adaptation: Detection-to-Detection (DET-DET)

Table 1 shows the results of DET-DET pipeline. For IR detection (ISDD), the Faster R-CNN with the VGG model, when trained and tested exclusively on IR data (baseline), severely underfitted, achieving low Recall (21.73%) and mAP (3.53%). After integrating SAR features (HRSID), substantial improvements were observed, with Recall increasing by approximately 19.3% and mAP by approximately 23.7%. In contrast, using IR data to improve SAR detection resulted in only a modest increase of around 1%, as the models trained and tested solely on SAR data (baseline) were not underfitting.

Adaptation Scenario	Recall (%)		mAP (%)	
	Baseline	Ours	Baseline	Ours
SAR→IR (**ISDD**)	21.73	41 (+19.3) ▲	3.53	27.26 (+23.7 ▲)
IR→SAR (**HRSID**)	39.97	40.91 (+1.0) ▲	32.64	33.52 (+1.0 ▲)

Table 1. Detection-to-detection results; bold indicates target dataset. Improvements (%) shown in parentheses.

3.2. Cross-task Adaptation: Classification-to-Detection (CLS-DET) and Vice Versa (DET-CLS)

Table 2 shows the results for cross-task experiments. For CLS-DET, training the VGG16 backbone initially on SAR classification data (FuSAR) and then fine-tuning for IR detection (ISDD) resulted in significant performance gains, with Recall improving by approximately 17% and mAP by approximately 20%. Conversely in DET-CLS, when initially training on IR detection data and then fine-tuning for SAR classification, the F1-score increased by 3%, demonstrating beneficial but smaller cross-domain improvements.

Training Approach	Baseline (%)	Ours (%)	Metric
SAR Classification → IR Detection (**ISDD**)	21.73	↑ 38.95 (+17 ▲)	Recall
SAR Classification → IR Detection (**ISDD**)	3.532	↑ 23.521 (+20 ▲)	mAP
IR Detection → SAR Classification (**Fusar**)	56.35	↑ 59.63 (+3 ▲)	F1-Score

Table 2. Cross-task results. Bold = target dataset, improvements (%) over baseline = ▲.

4. Discussion

We investigated two primary domain adaptation scenarios: same task (Detection-to-Detection) and Cross-task (between classification and detection). Our results clearly illustrate that integrating SAR data significantly enhances IR detection performance. Specifically, SAR provided robust features, effectively addressing the underfitting observed in IR-only models, as evidenced by the marked improvements in mAP and Recall metrics.

In the Detection-to-Detection scenario, substantial gains in IR performance highlight the advantage of transferring feature representations from SAR to IR. The minimal improvement from IR to SAR suggests that SAR datasets inherently contain richer and more diverse features, making them benefit less of complementary/different domain information.

Cross-task experiments also showed valuable insights. The transfer of features from SAR classification to IR detection tasks considerably improved IR performance, demonstrating effective feature generalization across tasks. Similarly, utilizing IR detection data for SAR classification, although beneficial, resulted in smaller improvements (approximately 3%), reflecting the limited feature complexity in IR data relative to SAR.

Overall, our findings emphasize the interoperability and mutual benefit between SAR and IR domains, particularly in scenarios with limited data. Future work will explore different DL architectures, additional SAR and IR datasets, and investigate the impact of geographic and temporal similarity of data sources on model performance.

5. Conclusions

Our experiments demonstrated that integrating SAR data significantly enhances IR ship detection performance, increasing mAP by over 20% and Recall by more than 17%. For SAR-based tasks, the improvements were modest but consistent, with increases of 3%, 1%, and 1% in F1-score, Recall, and mAP, respectively. These findings highlight the complementary relationship between SAR and IR data, confirming that domain adaptation effectively mitigates challenges related to data scarcity. Future research will explore additional SAR and IR datasets from geographically and temporally similar conditions to further validate and refine our approach. Overall, this study contributes towards more robust DL solutions in maritime surveillance applications facing limited data availability.

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Data Availability Statement: The code is available at https://github.com/cm-awais/sar_infra_domain_adaptation.

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