Crested Polar Lights Optimization enabled Light Weight Relevance Capsule Network for Synthetic Aperture Radar image object classification.

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Abstract: To ensure continuous all-weather observation, synthetic aperture radar imagery is generated, but the large volume of data generated poses a challenge. Although DL (deep learning) models have proven to be performant at classification tasks, they usually require a high amount of storage and computational power. As a result, their deployment on mobile or edge devices is non-trivial. Moreover, the speckle noise and complicated backscattering due to the inherent SAR characteristics make accurate feature extraction difficult. In light of the above limitations, this study proposes a Crested Polar Lights Optimization-enabled Lightweight Relevance Capsule Network (CPO-LWRCapsNet) framework.As discussed, the pipeline starts by denoting the input SAR images with the help of a guided filter. Then it processes using the DHT. Next, object segmentation takes place through the Kolmogorov–Arnold Network-Driven Multiscale Synergy Network (Disney), followed by robust descriptor generation using the Relative Directional Edge Binary Patterns (RDEBP). The CPO-LWRCapsNet is a hybrid of the Crested Porcupine Optimizer (CPO) and Polar Lights Optimization (PLO). In this optimization, the RACapsNet, which is a relevance-aware capsule network, is optimized with this hybrid approach. This multi-objective optimization ensures high accuracy of classification while tuning for low parameters like memory, Flops, etc., making SAR object classification real-time yet low in complexity.

Keywords: Synthetic Aperture Radar (SAR), Deep Learning-Based Classification, Lightweight Capsule Networks, Optimization Algorithms (CPO–PLO), Real-Time Edge Deployment

Introduction

Synthetic Aperture Radar (SAR), an active microwave sensor onboard either space-borne or air- borne, illuminates the target with a focused, directional beam of energy, producing unique scattering effect depending on the orientation of the sensed objects. With enormous volumes of data produced from SAR and many other SAR carrying satellites, the processing and interpretation of SAR data have become immediate for a wide range of applications. The SAR data are worth processing because of the advantages it offers. SAR is a radar attached to air-crafts or any other moving platforms and is used to construct images from the returned signals of the electromagnetic waves that it transmits to the earth’s surface. SAR can operate regardless of weather situations and with no time constraints. The images obtained from SAR have been applied to numerous applications, that include military surveillance, disaster management, maritime vigilance, inspection of illegal mining activities, etc., [1]. With more SAR sensors mounted satellites emerging in the coming years, gigantic data needs to be processed, archived and analyzed. Accessibility of such SAR data is challenging as they are difficult to interpret. One of the major processing steps of SAR images is classification, since classification is portable in categorizing the detected targets based on their classes [2]. Due to low spatial resolution and vulnerability to atmospheric interference, the accuracy of intelligent interpretation using Hyperspectral Image (HIS) is difficult. But SAR monitors the target area by transmitting and receiving echo information. In addition, SAR has the advantage of all-time and all-weather observation, which effectively makes up for the limited observation of HSI in bad weather [3].

SAR image classification is a basic task, aiming to assign the semantic label to each SAR image patch. Some conventional theory-driven approaches were explored to extract the hand-crafted features based on the expertise of SAR, e.g., the statistic model and the physical model-based methods. These model-based approaches have strong interpretability, yet the feature selection and classifier design are time-consuming and lack flexibility. As a comparison, the data-driven Deep Learning (DL) approaches can build an end-to-end system to learn the hierarchical features automatically and predict the semantic labels simultaneously without human intervention, superior to the pure model-based methods on SAR image classification tasks [4]. SAR has been widely deployed in various missions. As the most basic branch of SAR Automatic Target Recognition (SAR-ATR), the effectiveness of image classification algorithms directly affects the further interpretation of SAR images. The rapid development of DL in computer vision has inspired researchers to apply DL algorithms in the field of SAR and obtained outstanding performance beyond traditional methods [5]. SAR image classification has become an important research issue since these images from RADARSAT-2, ALOS PALSAR, Terra SAR-X, and ENVISATASAR have been made available. POLSAR images play a vital role in land-cover management due to their unique capabilities, including image acquisition in day and night and a weather data acquisition system [6]. SAR images have inherent speckle noise. Speckle noise changes the gray value of SAR image pixels randomly, which reduces the validity and distinguishability of features and affects network performance on SAR image classification. The ambiguity and instability of targets characteristics in SAR images are serious [7].

SAR images of the targets vary severely with the incident angle, azimuth angle, wavelength, and polarization. Moreover, there may be complicated interactions among different parts of the targets, resulting in severe phenomena of the same object with different spectra and different objects with the same spectrum [7]. While deeper networks can improve accuracy, they also introduce efficiency issues, characterized by a trade-off between accuracy and efficiency. Traditional Deep Neural Networks (DNNs) are quite challenging to deploy on mobile devices due to their high demands for storage and computing resources [8]. Despite the outstanding advantages of DL models, there is still a fatal drawback, i.e., large precisely labeled datasets and high-performance computers are needed to achieve acceptable classification accuracy, high training cost due to a large number of unlabeled data for training process in semi-supervised method [9]. To augment the image processing capabilities and efficiency of mobile devices within the constraints of limited storage and energy consumption, the development of lightweight DNNs is paramount. These networks are specifically tailored for resource-constrained environments, achieving a streamlined transformation of DL models. This endeavor involves addressing the limitations imposed by energy consumption, computational power, and memory on such hardware. It also necessitates a reduction in storage demands and computational overhead through the application of innovative architectural designs and model compression techniques, without compromising the accuracy of the models [8]. Techniques with efficient architectures are commonly used to achieve light weight DL, enabling real-time applications, such as object detection, and language processing to run effectively on low-power devices. Light weight DL framework classifies SAR images with limited computation [10].

Literature Survey

This section describes the literature survey of various existing techniques for SAR image object classification.

Authors	Methods	Advantages	Disadvantages
Noor Rahman, et al. [11]	Lightweight Synthetic Aperture Radar Network (LSARNet)	LSARNet prioritized the extraction of salient features over simply deepening the network, enabling efficient classification with minimal layers and reduced computational overhead.	The performance of this model was limited on more complex or challenging datasets, such as SOC10, with reduced generalization while handling high-variability SAR images.
Hao Pei, et al. [12]	Two-stage algorithm based on Contrastive Learning (CL)	This technique reduced the reliance on large labeled datasets, which are often scarce in SAR applications, remaining more robust.	CL methods often required large batch sizes and extensive training time, that was resource-intensive.
Jiseok Yoon, et al. [13]	Hybrid Conv-Attention Network	This model effectively captured both local spatial features and global contextual information, leading to improved recognition accuracy on complex SAR imagery.	This technique required more memory and processing power, making the real-time applications more difficult.
Noor Rahman, et al. [14]	Robust ensemble classifier	As ensemble classifiers combined multiple models, they remained reliable for SAR target classification across diverse operational conditions and variations in target appearance.	Ensemble classifier remained time-consuming in training and required careful hyperparameter management.
Jia Zheng, et al. [15]	Singular Value Decomposition-based Feature Reconstruction Module (SFRM)	This approach utilized very limited labeled data by leveraging feature reconstruction, making it well-suited for few-shot scenarios.	Failed to introduce back ground suppression methods, such as background segmentation strategies or attention mechanisms to improve robustness.
Jia Zheng, et al. [16]	Position-Aware Graph Neural Network (PA-GNN)	PA-GNN enhanced the similarity within the same class and increased the	Building and maintaining the graph, especially for large datasets was computationally

		dissimilarity between different classes in the embedding space, that effectively increased classification accuracy.	expensive and increased scalability issues.
Gui Gao, et al. [17]	SAR imaging with Lightweight Receptor field feature convolution, Bottleneck transformers and a Probabilistic intersection-over-union Network (R-LRBPNet)	This model combined lightweight architecture with SAR-specific feature extraction tailored for ship detection, enabling fast and efficient processing without the need for heavy computational resources.	This model failed to investigate more suitable loss functions for angle regression.
Junfei Shi, et al. [18]	Lightweight DeeplabV3+ network	This model effectively fused spatial and polarimetric information through attention-guided feature integration, enhancing the model's ability to distinguish subtle differences between SAR image classes.	Failed to incorporate mutual information to thoroughly exploit relationships among various features, thereby enhancing feature selection.

Challenges

The challenges faced by existing techniques on SAR image object classification are given below,

- In [11], a lightweight CNN based SAR image classification, termed LSARNet downsampled the feature maps and captured essential information. Even though, this model failed to smoothen the homogeneous areas without blurring object boundaries.
- SAR Imagery based Target Recognition using Hybrid Conv-Attention Network was developed in [13], that extracted local and global patterns in the image in an effective way. But this model failed to reduce the speckle noise, that reduced the performance of model.
- An enhanced ensemble classification framework for SAR Automatic Target classification under diverse operational conditions was developed in [14], that effectively reduced the impact of errors made by individual classifiers. Nevertheless, this technique heavily depends on high quality datasets.
- In [15], SFRM with Active Contrast Loss for Few-Shot SAR target recognition was developed maximizing the interclass feature distance, while minimizing the intraclass feature variance to the greatest extent possible. But this technique failed to capture the highly nonlinear scattering behaviours in SAR data.

- SAR image classification faces challenges arising from its coherent imaging characteristics and complex backscattering behavior, including speckle noise, nonlinear scattering effects, and domain-specific variations, that complicate accurate feature extraction and target discrimination.

Knowledge gap and Method

SAR image classification using light weight DL refers to the use of compact and computationally efficient neural network architectures to automatically identify and categorize features or targets in SAR imagery. These models are designed to deliver high classification accuracy while minimizing computational cost, memory usage, and energy consumption, making them suitable for real-time processing on satellites, Unmanned Aerial Vehicles (UAVs), and edge devices. The key advantages include faster inference, easier deployment on resource-limited platforms, and reduced training time. However, challenges remain, such as potential accuracy loss due to model compression, difficulty in handling SAR-specific issues, like speckle noise and limited labeled data, and reduced generalization across varying sensors and imaging conditions. To overcome these limitations, the Crested Polar Lights Optimization enabled Light Weight Relevance Capsule Network (CPLO-LWRCapsNet) is proposed for SAR image object classification. Initially input SAR Image will be acquired from the dataset [19], and this SAR image will be allowed for denoising using Guided filter [20]. Next, image transformation will be done using Discrete Hartley Transform (DHT) [21], and then, object segmentation will be carried out using Kolmogorov–Arnold Network-Driven Multiscale Synergy Network (KDMSNet) [22]. Further, descriptor generation will be carried out utilizing Relative Directional Edge Binary Patterns (RDEBP) [23]. Finally, the object classification will be performed using proposed CPLO- LWRCapsNet. Here, the architecture of Relevance Aware Capsule Network (RACapsNet) [24] will be optimized using CPLO, which will be formed by the combination of Crested Porcupine Optimizer (CPO) [25] and Polar Lights Optimization (PLO) [26], by considering multi objectives quality measure, like accuracy and light weight parameters, like memory, Floating Point Operations (FLOP), and so on. Figure 1 shows the block diagram of proposed CPLO-LWRCapsNet for SAR image object classification. The implementation of the developed model will be carried out in python tool using MSTAR Dataset 10 Classes [19]. The performance of the proposed CPLO-LWRCapsNet will be evaluated using evaluation metrics, such as accuracy, True Positive Rate (TPR), and True Negative Rate (TNR). Then, the proposed method will be compared with that of existing works in order to reveal the efficiency of proposed CPLO-LWRCapsNet.

Objectives

The major objectives of this proposed system are listed as follows:

- To denoise SAR image using guided filter for suppressing speckle noise, while retaining structural details and edges for improved image quality.
- To perform image transformation utilizing DHT for enabling efficient analysis, filtering, or feature extraction.
- To segment the object with KDMSNet for accurately delineating object boundaries in images while efficiently capturing both local and global contextual information.

- To perform descriptor generation using RDEBP for extracting robust and discriminative feature representations from images by combining rotation-invariant, dense, and enhanced binary patterns for effective recognition and matching tasks.
- To detect the object using proposed CPLO-LWRCapsNet for efficient, and accurate object detection by capturing spatial hierarchies and feature relevance while minimizing computational complexity.

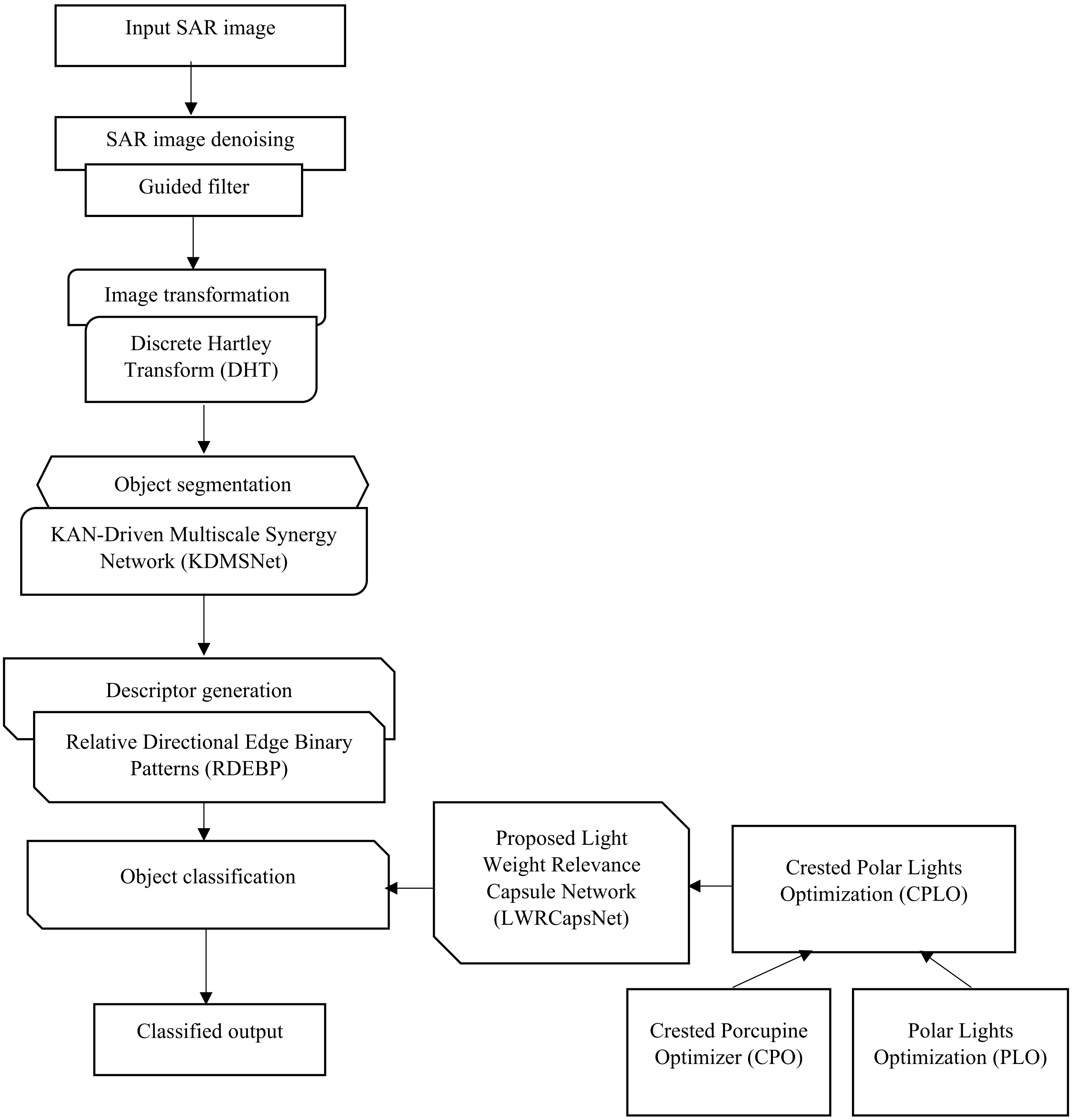

Figure 1. Block diagram of proposed CPLO-LWRCapsNet for SAR image object classification

Conclusion

Synthetic Aperture Radar (SAR) imagery is necessary for continuous, all-weather observation across a variety of critical applications, but it remains very challenging to decode such large volumes of data. Many deep learning networks (DL) have significantly advanced sonar automatic target recognition (SAR ATR), but conventional deep neural networks pose major deployment issues on a resource-constrained platform like a UAV or edge devices due to high computational cost, memory requirement, and energy expenditure. In addition, streaks, distinctive scattering characteristics, and restricted labelled datasets constantly hinder accurate classification of SAR. In order to resolve these operational and computational bottlenecks,s this study presents a novel framework, the Crested Polar Lights Optimization enabled Lightweight Relevance Capsule Network (CPO-LWRCapsNet). The methodology includes a complete pipeline for speckle noise removal using the Guided filter, image conversion in Discrete Hartley Transform, object segmentation using Disney, and descriptor generation using Relative Directional Edge Binary Pattern. The proposed system combines a Relevance Aware Capsule Network (RACapsNet) and a hybrid Crested Polar Lights Optimization (CPO) algorithm. The proposed system achieves high classification accuracy with low complexity. It can efficiently classify objects in real time from SAR images.

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