Automatic Target Recognition in SAR Using Deep Learning

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Abstract - The project uses many useful deep learning methods to automatically recognize targets in SAR images and relies on the well-known MSTAR dataset. In defense and surveillance, radar systems in many sectors are valuable and important because they capture high-resolution target images in any weather or lighting conditions. One of the main goal of this project is to assess how well CNN-based models can recognize military targets in this SAR images. The study looks at how effective CNNs are at identifying targets when the radar captures them from different angles and positions. Instead of using manually crafted features, the CNN learns directly from the SAR images to classify various types of military targets, even when the images have speckle noise or other distortions. To improve accuracy and flexibility, the model also uses data augmentation and normalization techniques. The results of the project execute and shows that deep learning provides a reliable way for real-time recognition and classification of targets using radar data.

Key Words: Synthetic Aperture Radar, Automatic Target Recognition, Deep Learning, Convolutional Neural Network.

1.INTRODUCTION:

Automatic Target Recognition (ATR) has become an essential component of modern defense and security systems. Its primary goal is to detect, recognize, and classify objects with minimal human involvement[3]. This features makes SAR a valuable tool for military surveillance and battlefield observation. Interpreting these images can be difficult and challenging due to speckle noise, background interference, and the lack of natural optical features.

Deep learning methods have proven to be highly effective in addressing these challenges. CNN's in particular, are well-suited for image recognition tasks as they learn hierarchical features directly from raw data. When applied to SAR imagery, CNNs can identify meaningful patterns and improve classification accuracy, even under complex imaging conditions.

Deep learning techniques are explored for ATR using the well-known MSTAR dataset. This dataset contains SAR images of various military vehicles captured from different angles and settings, making it suitable for evaluating recognition models.

2. Literature Review

ATR using SAR images has become an important research area by its various uses in defense and surveillance. Unlike regular optical images, these images are harder to interpret. They often contain noise and are affected by environmental conditions. Earlier methods for recognizing SAR images relied on manual feature extraction and processing, which made them slower, less accurate, and not suitable for real-time use in complex situations.

One main issue with SAR images is speckle noise. This noise reduces clarity and lowers recognition accuracy. To improve performance, modern approaches often use denoising methods before training deep learning models. By reducing noise, CNNs can capture more meaningful features and deliver more accurate results.

In addition, new CNN designs, along with techniques like data augmentation, help improve generalization. Techniques such as flipping, rotating, or adding synthetic distortions create more varied training samples [1]. This makes the models resilient to changes in viewing angles and imaging conditions.

Overall, deep learning, especially CNN-based methods, has significantly improved the reliability of ATR in SAR imagery. When combined with some important preprocessing techniques which are noise reduction and training strategies such as augmentation, these models achieve high recognition accuracy and get closer to practical, real-world defence applications.

3. DATASET:

This study uses the well-known MSTAR dataset, which is widely accepted for evaluating target recognition in SAR images[5]. It was originally created through a DARPA-funded program and includes high-resolution SAR images of various military ground vehicles collected in controlled settings. Over time, it has become the standard reference for testing and validating SAR-based ATR models.

The images in MSTAR have a resolution of 0.3 m by 0.3 m and are typically sized at 158 by 158 pixels[5]. The dataset includes a wide range of vehicle classes, such as tanks, trucks, missile launchers, and armored personnel carriers. To reflect real-world scenarios, the vehicles different angles are captured and positions. For evaluation, the given dataset is split into two training and testing, using a consistent protocol.

In this research, two recognition tasks are explored: a simpler three-class classification and a more complex ten-class classification[1]. Following standard practice, training uses images captured at a 17° depression angle, while testing uses images taken at 15°. This approach tests and tells how well the models can handle slight differences in imaging conditions.

A significant challenge in SAR imagery is speckle noise, which reduces recognition accuracy. To tackle this, denoising is been applied to raw images before training. To further improve performance, augmentation methods like flipping, rotation and scaling are used. These methods increase the variety of training samples and reduce overfitting. Together, these preprocessing steps make the models more reliable and capable of generalizing to unseen targets.

4.SAR Images Characteristics and Challenges

SAR is a method that produces high-resolution two-dimensional images using microwave radar signals. Unlike optical imaging systems, SAR can capture images in any weather and at any time of day [6]. This ability is vital for defence surveillance, reconnaissance, and intelligence operations. However, SAR imagery has specific challenges that complicate automatic target recognition (ATR), especially when we are using machine learning or some deep learning techniques.

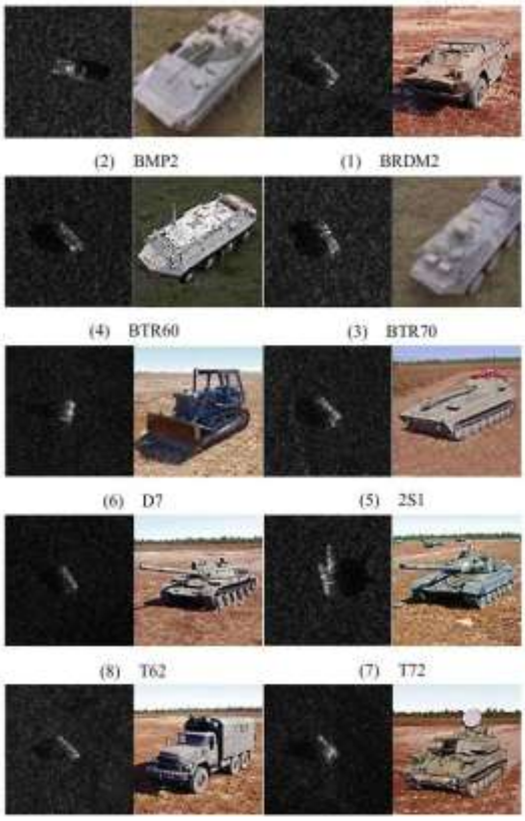

Figure 1. These are Ten types of targets in SAR images and their corresponding optical images on right.

One major issue is coherent speckle noise. This noise arises from the interference of radar wave reflections, creating a multiplicative effect. Speckle reduces image clarity, distorts structural details, and makes it harder to extract and classify features. Furthermore, the spatial correlation caused by speckle can confuse CNNs during training if not addressed correctly.

One of the other challenges comes from changes in imaging geometry, particularly azimuth and depression angles[10]. The same object might appear different depending on the radar's position, resulting in high variability within the same class. This variability makes it hard for models to generalize unless they train on various targets.

Unlike other images, SAR images only show the backscatter intensity of objects[4]. They do not include some of the elements like colour, shadow, and texture. This absence increases the need for preprocessing, feature engineering, and data augmentation to extract useful information.

Additionally, background clutter, occlusions, and overlapping objects can make it difficult to distinguish targets from their surroundings. A low signal-to-noise ratio (SNR) in some of the it cases can also reduce the

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contrast between targets and the background, complicating detection and classification.

These are the challenges highlight the need for better denoising techniques and CNN designs that focus on spatial consistency and multi-scale feature extraction. By tackling these inherent difficulties, researchers can also develop a more and more robust deep learning systems, making SAR-based ATR methods more practical and effective in real-world defence scenarios.

5. Methodology:

The process of Automatic Target Recognition (ATR) in SAR using deep learning follows a clear, step-by-step pipeline. This involves preparing the data, training the model, evaluating its performance, and moving toward deployment. The MSTAR dataset is used throughout this work to ensure results are reliable and comparable with existing studies.

1) Data Collection:

The MSTAR dataset provides high-resolution SAR images of different military ground vehicles. Each image is also labelled with the correct class. The dataset includes variations in viewing angles, environmental conditions, and terrains.[8] This diversity forms a better foundation for some training some deep learning models that need to work well in real-world defence applications.

2) Data Preprocessing:

Before training, raw SAR images are cleaned and standardized. First, pixel values should be normalized to [0,1] range, which helps reduce differences between samples. To address speckle noise, a common issue in SAR images, denoising techniques like non-local means filtering or advanced deep learning filters such as DnCNN are applied. The given images are then resized to fixed dimension for compatibility with neural networks. This creates a more varied training set and reduces overfitting.

3) Feature Extraction with CNNs:

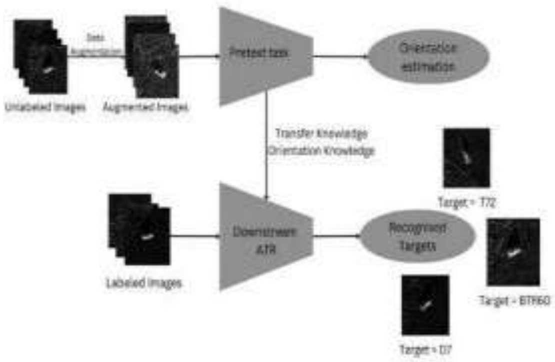
CNNs automatically extract key patterns from the images. The network includes multiple convolutional and pooling layers that capture spatial features at different levels [6]. Activation functions like ReLU help the network learn complex relationships.

4) Model Training:

The given dataset is divided into training and validation sets, typically in a 70:30 ratio[9]. The CNN is trained using the categorical cross-entropy loss function and optimized with the Adam optimizer. Training occurs over several epochs with a defined batch size, and performance is tracked using some of the metrics such as accuracy and loss. Techniques like dropout and batch normalization are included to improve the model's flexibility and also prevent overfitting.

5) Model Evaluation and Inference:

After training, this model is tested on a another separate dataset to measure the accuracy, recall, precision, F1-score, and confusion matrix results. Once validated, the network is applied to unseen SAR images to classify targets effectively. For deployment in real-world systems, optimization methods like pruning and quantization are u used to improve the model's efficiency. Final outputs can be shown through performance dashboards, providing



useful insights for defence operations.

Figure 2. Architecture diagram of the proposed cnn-based sar atr system.

6. Proposed System:

The proposed system provides a framework for Automatic Target Recognition (ATR) in Synthetic Aperture Radar (SAR) imagery. It tackles the problem of limited labeled data. Unlike traditional methods that need large annotated datasets, this system employs a semi-supervised learning approach, which cuts down on extensive manual labeling. The workflow mainly consists of two main stages: unsupervised pretraining and supervised fine-tuning.

1) Unsupervised Pretraining:

In the first phase, the model uses a large set of unlabeled SAR images[2]. This enables these network to learn general patterns like shapes, orientations, and structural details without relying on labels. Techniques such as self-supervised or contrastive learning help create meaningful feature representations. By the result, the model gains a solid initial understanding of SAR image characteristics, which can be later refined for classification tasks.

2) Supervised Fine-Tuning:

In the next phase, pretrained model is fine-tuned with a smaller labeled dataset[12]. During this stage features are learned in pretraining are connected to specific target classes, including tanks, trucks, and armoured vehicles. This blend of broad representation learning and limited supervision increases classification accuracy while reducing the need for annotations.

3) Noise Reduction:

Since SAR images often have speckle noise, a denoising step is included in the preprocessing pipeline. This enhances image quality while preserving structural details, ensuring that the model focuses on key features instead of noise artifacts.

4) Overall:

This two-stage semi-supervised approach strikes a balance between accuracy, efficiency, and practicality. By decreasing reliance on labeled data and incorporating noise reduction, the system is well-suited for real-world SAR ATR applications where annotated samples are hard to find.

7. Future Works:

Although the proposed system shows promising results for automatic target recognition (ATR) in SAR imagery. One important area to explore is using semi-supervised and self-supervised learning techniques. For example, contrastive pretraining on larger volumes of unlabeled SAR data or using models like GANs and VAEs to create realistic training samples could improve model generalization and reduce the need for annotated datasets.

Another area for progress is transfer learning across some datasets and sensors. While the current study relies on the MSTAR dataset, applying the model to other SAR datasets with various environments, resolutions, or sensor specifications would make the system more robust and flexible for real-world conditions. Similarly, combining multi-modal data, such as SAR with optical or infrared imagery, could provide information that compensates for SAR's lack of color and texture cues, improving recognition performance.

Improving noise robustness and defending against adversarial attacks is also a promising path. SAR images often face severe speckle noise, background clutter, and even intentional signal interference in tough environments. Further research can also explore better denoising strategies and reliable training techniques to ensure model performance in these conditions.

From a practical standpoint, developing lightweight and efficient models for low-power embedded systems or unmanned aerial vehicles is important. Some techniques like model pruning and knowledge distillation can help reduce computational demands without significantly losing accuracy. At the same time, adapting the system for real-time ATR in streaming SAR data could enhance its usefulness in reconnaissance and surveillance tasks.

Lastly, there is a growing need for the explainability and interpretability models used for defense and surveillance. Further efforts could also focus on integrating explainable AI methods into SAR ATR systems to clarify model decisions. This would enhance trust and transparency for human analysts who rely on these systems in critical missions

8. Conclusion:

This research tells how deep learning can be effectively applied to ATR in SAR images using the MSTAR dataset. The results show that CNNs are highly capable of identifying and classifying military targets with strong accuracy. Their ability of automatically extract complex features makes reliable than traditional methods, even when dealing with noise, clutter, or changing imaging conditions.

The study also highlights the importance of preprocessing methods such as normalization, denoising, and data augmentation. These steps help improve model robustness by reducing the speckle noise and background interference, allowing the network to focus on meaningful structural patterns.

In summary, deep learning–based ATR systems present a powerful solution for defense and surveillance tasks that require accurate and real-time target recognition[7]. Future research can further strengthen these systems by exploring optimized CNN architectures, applying transfer learning, and combining SAR data with other modalities to improve performance and adaptability across different datasets, sensors, and real-world environments.

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