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Recognition for Targets Type of Synthetic Aperture Radar Imagery using Deep Learning Methods

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ABSTRACT

In recent years, Synthetic Aperture Radar (SAR) imagery has played a crucial role in various applications such as reconnaissance, surveillance, and target recognition. Deep learning methods have emerged as powerful tools for target recognition in SAR imagery due to their ability to automatically learn discriminative features from data. We review state-of-the-art techniques for dataset preparation, network architecture design, training strategies, and performance evaluation in SAR target recognition tasks. Achieving a verification accuracy of around 97% for an eight-class classifier is remarkably impressive. In addition, the similarity between training and validation accuracy indicates the strength of our classifier. Overfitting, which has much higher training accuracy compared to validation accuracy, is a concern The depicted image outlines the training process. In the upper plot, the dark blue line represents the model's accuracy on the training data, while the black dashed line illustrates its accuracy on the separate validation data. Achieving a validation accuracy of nearly 97% for an eight-class classifier is notably impressive. Additionally, the similarity between the training and validation accuracies indicates the robustness of our classifier. The ZSU-23/4 class appears to present the most difficulty for the model among the eight classes. Due to similarities in SAR images, instances of misclassification occur between the ZSU-23/4 and 2S1 classes. Nonetheless, the model demonstrates the capability to achieve accuracy levels exceeding 90% for this class.

1. Introduction

As cities continue to expand, increasing population density and traffic volume have become major contributors to urban road congestion [1]. Synthetic Aperture Radar (SAR) imagery is widely used in the Joint Intelligence, Surveillance, and Reconnaissance (JISR) domain to generate the so-called Recognised Ground Picture (RGP). Raw SAR data is being used by analysts to answer to intelligence needs, which often involve identifying targets of interest or notable behaviours. Even highly skilled analysts have trouble identifying and classifying targets when trying to visually estimate their shape from SAR photographs [2]. In Synthetic aperture radar imaging, or SARI, has been extensively used in many fields, such as environmental studies, earth's water studies, terrain, and oceanic

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phenomena. SARI is essential for giving images of the planet's surface for military purposes. Despite SAR's ability to produce images with high resolution, images are typically attenuated by speckle noise caused by imaging equipment, which can make data interpretation challenging. Speckle noise is a multiplicative form of noise that is created by resolving unit interference echo. Therefore, it could be difficult for even very experienced translators to identify crucial portions in the images [3]. CNNs into the data domain of synthetic aperture radar (SAR) without using transfer learning. By clustering its neuron layers, fusing the features extracted from the hidden layers to bridge the gap between the visual and SAR modality, and utilising a local feature matching scheme, our SAR automatic target recognition (ATR) architecture effectively extends the pre-trained Visual Geometry Group CNN from the visual domain into the X-band SAR data domain [4]. In Khalid *et al*., [5], a group of researchers has delivered a comprehensive state-of-the-art review on automatic target recognition in synthetic aperture radar imagery (SAR-ATR). Our analysis indicates that the low-level classification (LLC) stage commonly employs a feature-based classifier, while the high-level classification (HLC) stage is founded on one of the three mentioned approaches.

A straightforward statistical filter with a nonlinear function is used to eliminate speckle noise from digital photos while maintaining the edges. The recommended filter outperforms conventional speckle noise reduction filters in the restoration of the SAR picture, according to experimental data. A team of researchers [6] introduced a novel simulation program featuring advanced technology for categorizing military aircraft by utilizing multiple leakproof radar images captured of targets at specific moments. These images are then fed into our convolutional neural network (CNN). The research suggests that having more than four radars in such an array yields results nearly as accurate as those obtained under optimal climatic and lighting conditions [6].

Kalkidan Gezahegn *et al*., [7]'s model introduced a batch normalization operation following the convolutional operation, which is then followed by the ReLU activation function. ReLU demonstrates superior performance without requiring unsupervised training for labeled SAR data, thereby reducing training time. In 2020, Cristian Coman and Rene ThaensIn [2] offered an automated target recognition (ATR) technique for Synthetic Aperture Radar (SAR) pictures. When it comes to formal feature extraction, classical machine learning algorithms have not performed as well as deep convolutional neural networks (CNN) classifiers on benchmark datasets like MSTAR. Designing Recognised Ground Planes (RGP) that are ready for production requires the application of CNN-specific methodologies. In another study [1], enhancements have been made to the YOLOv4 algorithm for detecting and tracking vehicles. The average accuracy for vehicle recognition has been improved to 88.5%, and the real-time frames per second (FPS) has reached 30, meeting the criteria for real-time vehicle detection.

Li *et al*., [8] described in details related to ship detection methods in SAR images: their history, present, and future based on deep learning. Before SSDD became available on December 1, 2017, the history of SAR ship detection is examined. This section primarily examines the significant benefits of deep learning-based algorithms and presents the CFAR-based detection technique. Moreover, theoretical and experimental comparisons are made between them. This is followed by a thorough summary of the most recent (as of December 1, 2017) deep learning-based ship identification systems. It is stressed that the key task for the future is to close the gap between computer vision and SAR ship detection by creating standards and combining the tiny datasets now available into a bigger one. The study presented a simulation model for tracking ground vehicles using optical flow, focusing on vehicle tracking and identification for traffic control. The model used optical flow for motion estimation, a median filter for noise reduction, and morphological processing for encircling moving vehicles. Future research may focus on real-time speed detection and vehicle recognition [9]. In a paper by Ekbal *et al*., [10], they presented a novel method for localizing iris features using median filter, histogram analysis, and semi-discrete matrix decomposition. It compares neural networks (NN) and convolutional neural networks (CNN) and shows high classification accuracy of 95.5%, outperforming existing literature and reducing localization time [10].

2. Synthetic Aperture Radar Data

Radars deployed in aircraft for Earth observation missions use azimuth and range compression to provide high-resolution pictures of observed scenes. Microwave radar wave pictures are shown in the complex domain using amplitude and phase data. The radar reflectivity is shown by the amplitude information, which is often displayed as a black-and-white image. An analyst finds it more challenging to understand phase information, which is frequently hidden from view on the radar display. Nevertheless, the phase includes target information that can be used to identify and categorize objects in SAR data using further feature extraction algorithms [2].

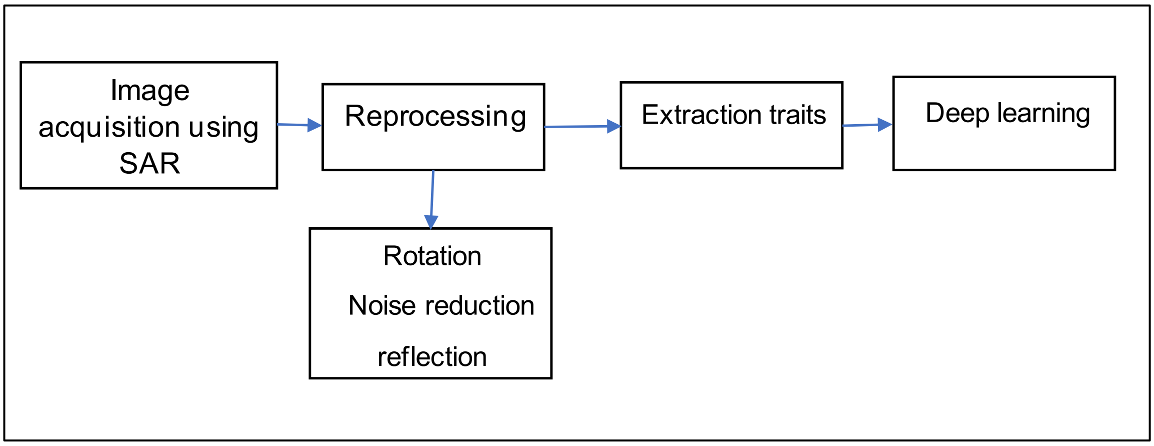

Fig. 1. A system's overall architecture for SAR-ATR

3. Automatic Target Recognition in the Sar Context (Sar-Atr)

By employing one or multiple sensors directed toward a designated scene, Automatic Target Recognition (ATR) regulates data output. This process typically entails utilizing computational power to identify target categories within sensor data and, alternatively, to characterize specific attributes of interest such as articulation, orientation, occlusion, sub-class, etc., without human intervention. The acronym ATR originated from the military program Low Altitude Navigation and Targeting Infrared for Night (LANTRIN) in the mid-1980s, and its significance has since expanded to encompass both military and civilian applications. ATR represents a subset of machine vision, addressing the broader challenge of programming computers to execute tasks typically performed by humans [7].

4. Deep Learning Neural Networks

Employing numerous tiers of nonlinear processing stages that naturally form a hierarchy, deep learning encompasses a diverse range of machine learning structures and methodologies. Depending on their intended applications, deep learning methods and architectures can be categorized into three group [11]:

1. Generative deep structures, which aim to describe joint statistical distributions of observable data and their associated classes, or the higher-order correlation properties of the data. Such architectures can transition to being discriminative by implementing the Bayes rule.
2. Discriminative deep architectures, which aim to enhance discriminative capability for pattern classification by specifying posterior distributions for the classes based on available data.
3- Hybrid deep architectures, Advanced regularisation and/or optimisation techniques enable hybrid deep architectures, whose primary goal is discrimination, to benefit (sometimes significantly) from the output of generative architectures.

5. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) has exhibited satisfactory performance in processing 2D data featuring grid-like structures, such as images and videos, and is considered a subtype of discriminative deep architecture. Deep 2-D CNNs, characterized by millions of parameters and multiple hidden layers, have the capability to learn intricate patterns and objects, particularly when trained on extensive visual databases with labeled ground truth representations. These distinctive capabilities, coupled with appropriate training, render them a valuable tool for various 2-D signal engineering tasks, encompassing images and video frames. Inspired by the visible cortex in the human brain, which comprises numerous cells responsible for detecting light within small, overlapping subregions, CNN's design draws parallels with this biological mechanism [12].

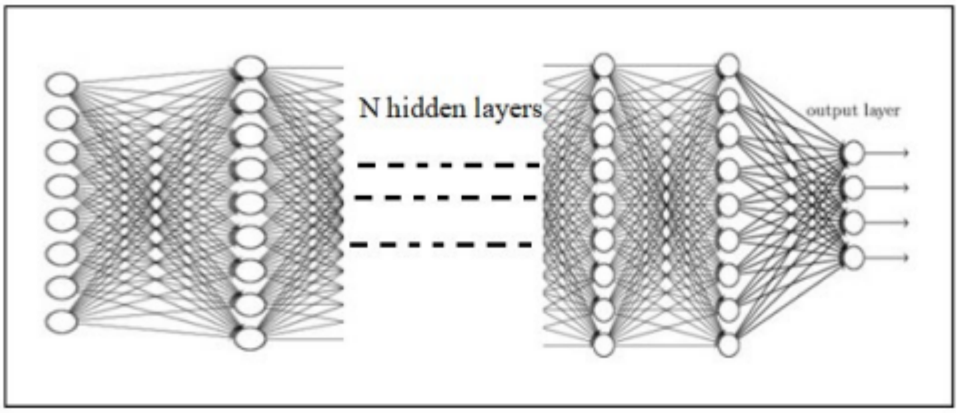

Fig. 2. Deep neural network layers [12]

In this instance, the MSTAR target collection comprises 8688 Synthetic Aperture Radar (SAR) images depicting seven ground vehicles and a calibration target. The data were gathered using an X-band sensor operating in spotlight mode, providing a resolution of 1 foot. The selected target types for analysis include the BTR70 (armored car), T72 (tank), and BMP2 (infantry fighting vehicle). The images capture various aspect versions ranging from 190 to 300, ensuring full coverage of 360 degrees, at two distinct depression angles: 15 degrees and 17 degrees. The figure below illustrates both optical and SAR images of these three target categories alongside their corresponding replicated targets [12].

6. The Works

1. Utilize the provided URL to retrieve the dataset by employing the Download MSTAR Target Data helper function, as delineated at the conclusion of this example. The dataset size is 28MiB.
2. Image data download and analysis The MSTAR suite includes a calibration target as well as SAR results from seven ground vehicles. Optical images and SAR images of these eight targets are shown in Figure (3).
3. The images and their associated category labels are currently stored within the variable named "imds." The folder names housing the image files are automatically utilized to allocate labels. To ascertain the number of photographs within each category, employ the "countEachLabel" function, show in Figure (4) .
4. Begin by defining the network input size, considering both your system's memory constraints and the computational expense of training.
5. Create test, validation, and training subsets from the dataset. Allocate 10% of the dataset for testing after training, and assign the remaining 80% for training purposes. Utilize the "splitEachLabel" function to divide the "imds" datastore into three separate datastores: "imdsTrain," "imdsValidation," and "imdsTest." To maintain consistent class distributions across the training, validation, and test sets, the function adjusts for variations in the number of images belonging to different classes.
6. Specify the architecture of the convolutional neural network.
7. After constructing the network structure, establish the training options using the "trainingOptions" function from the Deep Learning Toolbox. Initiate training with a learning rate of 0.001 and utilize stochastic gradient descent with momentum (SGDM). Set the maximum number of epochs to three, where each epoch represents a complete training cycle on the entire dataset. Monitor the network's accuracy during training by providing validation data and specifying the validation frequency.
8. Train the network with training options, training data, and the layer-specific design. TrainNetwork utilises the Parallel Computing ToolboxTM, depicted in Figure (5), to effectively leverage a GPU with computing capacity 3.0 or more that is compatible with CUDA®. Central processing units, or CPUs, are substituted in the event that graphics processing units (GPUs) are not accessible. Use the "ExecutionEnvironment" name-value pair argument of the training options to further personalise the execution environment.

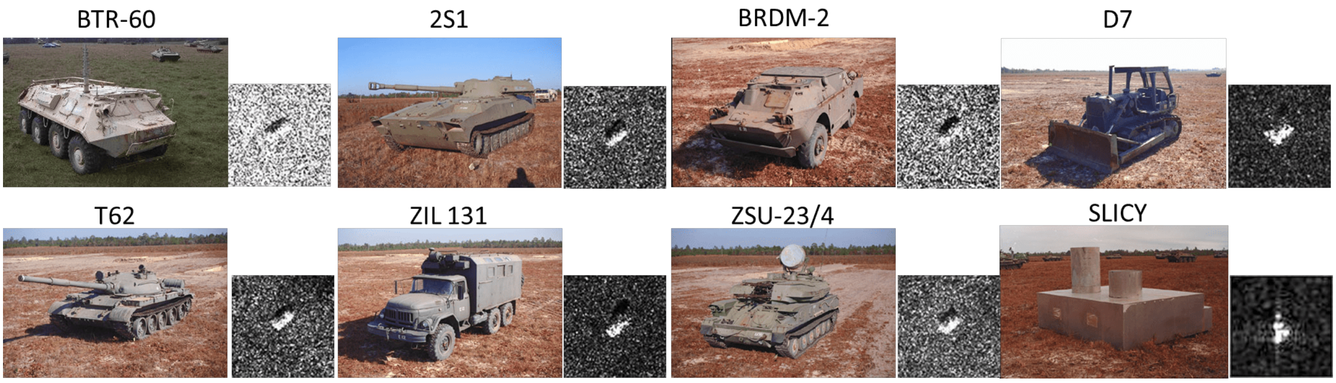

Fig. 3. Optical images and SAR images

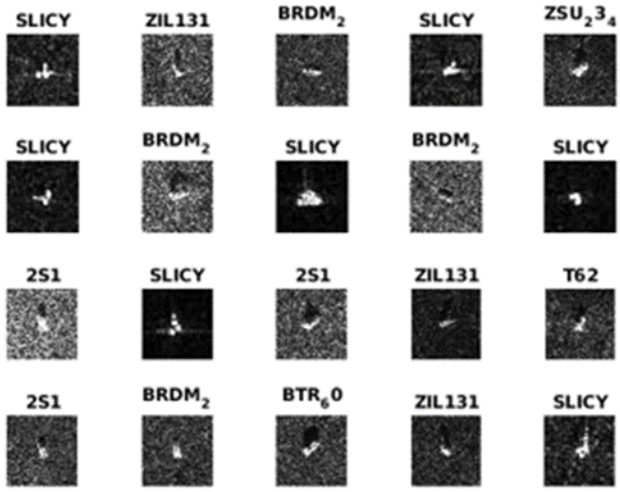

Fig. 4. Sample training images

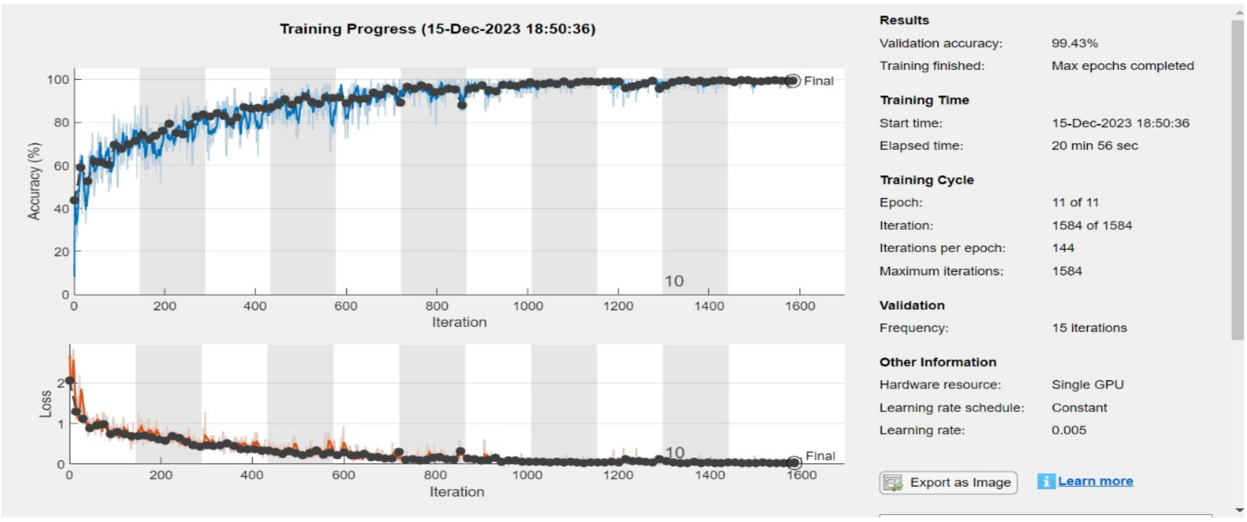

Fig. 5. Training progress

Table 1
Accuracy of training

Number of text	Learning Rate	Epoch	Iteration	Accuracy
1	0.001	3*3	432	97.24%
2	0.005	5*5	720	90.93%
3	0.005	7*7	1008	98.51%
4	0.005	9*9	1296	98.51%
5	0.005	11*11	1584	99.43%
6	0.01	11*11	1584	95.98%
7	0.01	7*7	1008	79.56%
8	0.05	7*7	1008	13.43%

7. Conclusions

Knowing and tracking targets is a necessary process in security and military applications, as well as in civil applications. The tracking process is carried out through SAR by taking aerial photographs, after which the images are filtered and the targets to be identified are identified. After the eight targets were tested: BTR70 (armored car), T72 (tank), and BMP2 (infantry fighting vehicle), T62, 2S1, D7, Slicy , Zli131, zsu_23_4. As shown in Figure 3, using the CNN method and the Matlab program, we conducted more than one test of the network by changing the learning rate. The best result was where the value was equal to (0.005) and the accuracy was equal to 99.43%.

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