Automatic Target Recognition and Classification from Synthetic Aperture Radar Imagery using Multi-Stream Convolution Neural Network

Kalkidan Gezahegn[1]*, Dr. Sudeshna Chakraborty[1]

[1]Department of Computer Science, Sharda university, Greater Noida, India

gezahegnkalkidan2015@gmail.com, sudeshna.chakraborty@sharda.ac.in

Abstract

The recognition of target is the process of discovering the location, pose and class of a target with a particular spatial signature by using a remotely sensed images, which belongs to a particular kind of object. The process of using computer to identify or recognize a target from Synthetic Aperture Radar (SAR) Images with or without human interference is known as Automatic Target Recognition (ATR). The traditional architecture of automatic target recognition for synthetic aperture radar consists of three stages: detection, discrimination, classification and recognition. In the last few years Many deep convolutional neural networks have been proposed and used for SAR-ATR and have obtained a state-of-the-art results in many computer vision tasks, plus shown improvement from time to time, but most of them classify targets from target chips found from SAR imagery, and used as a third stage (classification) of SAR-ATR traditional architecture in addition due to limited training images in SAR- ATR, CNN yielded over-fitting when directly applied to SAR-ATR. In other hand to make full use of limited SAR imagery this thesis present Multi-Stream CNN (MS-CNN) for end to end SAR-ATR which uses multiple views of SAR images. MS-CNN takes multiple views of the same target.

1 Introduction

Christian Hulsmeyer of Germany was the first person who granted the license from detecting object by using radio waves to identify the nearness of distant metallic objects. However before some times in 1886 Heinrich Hertz showed the reflection of radio waves from solid objects which utilized as a benchmark for many radio wave researchers at the time. Prior to World War II, specialists in nations, for example, France, Britain, Germany, and Japan worked subtly on creating advances that prompted current Day version of of radar. In 1934, stuff of American Naval Research Laboratory showed the principal radar as a pulsed system, at the same year, the British were the first to utilize radar for defensing against an air ship assault and in 1940 the term RADAR was strike by the United States Navy as a shortenings for RAdio Detection And Ranging.

SAR is radar working in microwave band and produces cognizant symbolism utilizing microwaves reflected from objects, under all climate, which has great properties and offers unmistakable dynamic remote detecting capacities for both military and regular citizen applications with ground-breaking potential. Since SAR is an active sensor, which gives its own illumination, it can accordingly work day or night; ready to illuminate with variable look point and can choose wide territory inclusion. The gathering of SAR pictures by different platforms (for example Global Hawk, NASA/JPL AIRSAR, and so forth.) and different missions for numerous reasons (for example observation, landscape mapping, and so on.) has prompted immense measure of information over wide reconnaissance zones. The pixel– to– eye proportion is just unreasonably high for human investigators to quickly filter through gigantic volumes of sensor information and yield commitment choices rapidly and definitely.

The standard architecture of an end to end ATR framework for SAR image (SAR-ATR), is depicted in Fig. 1. To account for the prohibitive amounts of processing to the input SAR imagery the system is to divide and conquer. The standard architecture of SAR-ATR processing is part into three distinctive stages: detection, discrimination, and classification. Detection (also called pre-screener): the primary phase of SAR ATR detects a region of interest (ROI) from a SAR image. Discrimination (also called low-level classifier, LLC): the second phase of SAR ATR discriminate whether a ROI is a target or non-target region, and outputs the discriminated ROI as a target chip. Classification (also known as high-level classifier, HLC): the third stage of SAR ATR classifies target classes from a target chip it includes Classification, Recognition, and Identification. The first two stages together are commonly known as the focus-of-attention module. It ought to be featured that (hypothetically) there is no limitation on the quantity of stages. Thus, Effective Automatic Target Recognition (ATR) calculations to process this developing pile of data are obviously required.

*gezahegnkalkidan2015@gmail.com

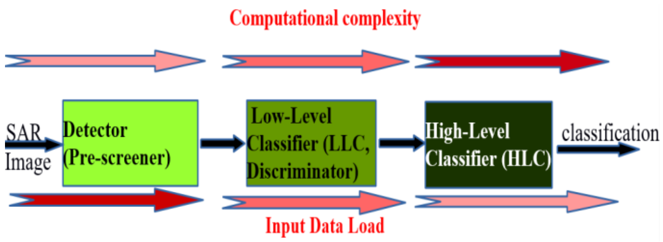

Fig. 1 General structure for an end-to-end SAR-ATR system.

As depicted in Fig. 1, the input SAR image creates an extremely high computational load due to its high resolution and/or the presence of various clutter types and objects. As the SAR data progresses throughout the SAR-ATR processing chain, its load is reduced. The HLC stage deals with SAR data that has relatively lower computational load. To the contrary, the computational complexity of the SAR-ATR chain increases as the SAR data progresses from the front-end stage toward the back-end stage. The remainder of this paper is organized as follows. In Section II, the topic of ATR is overviewed in the context of SAR imagery. In Section III and IV, the problem of statement and need for the research are introduced respectively. In Section V, a recent art of states are presented. In section VI proposed method explained. In the last section, section VII the dataset that uses for SAR-ATR tasks illustrated in table form.

2 Automatic Target Recognition in the SAR Context (SAR-ATR)

ATR manages the data yield from one (or more) sensor(s) aimed at a scene of interest. It generally refers to the utilization of computer processing capacities to derive the classes of the targets in the sensor data, and to (alternatively) characterize a few attributes of interests, for example, articulation, orientation, occlusion, sub-class, etc. . . without human interruption. The term ATR began in the military in the mid-1980s under the Low Altitude Navigation and Targeting Infrared for Night (LANTRIN) program. Today, ATR innovation is imperative in both military and civilian applications. The ATR issue is a piece of the general wide issue of machine vision; to be specific, *in what manner would computers be able to be arranged to do what people do productively and normally?*

Target, clutter and noise are three terms of military roots related with ATR, and relies upon the application of interest. On account of SAR imagery, target alludes to the object(s) of interest in the imaged scene. Clutter alludes to synthetic (building, vehicles, and so forth.) and additionally natural objects (trees, topological highlights, and so on.) that will in general dominate the imaged scene. Noise alludes to flaws in the SAR picture which are an aftereffect of electronic noise in the SAR sensor, as well as computational mistakes presented by the SAR signal processor. There is a range of ATR issues extending from classifying a pre-known mark in a well-characterized clutter to recognizing the source of signature that varies greatly with pose and state, and is located in a highly complex and probably occluded scene [20].

3 Statement of Problem

A major bottlenecks in military automatic target recognition is detecting or recognizing targets from imagery gathered by an imperfect sensors and the complexity of warfare and the requirement to reduce risks and maximize efficiency against difficult targets has increased the need for Automatic Target Recognition (ATR). No single sensor at present gives a sufficiently strong capacity of distinguishing all classes of target through the cover and misleading components of natural or potentially man-made mess. Battle target identification is additionally corrupted by other operational inconveniences, for example, climate, electronic condition, urban context, versa- tile targets, and the presence of bomb harm debris. Plus it is clear to see the inability to extract more information from sensors utilized in military activities.

4 Need for the Research

Many sensors like radar have a good potential to give far more information than currently extracted and process those information using Automatic Target Recognition (ATR) systems to help operators to make a better decision. However most of traditional Automatic Target Recognition (ATR) have a problem of removing useful target information instead of clutter, which leads to wrong knowledge about the target. ATR systems perform at very good level for images which have low clutter but for data with highly cluttered background the accuracy result is unacceptably low. Thus, it is important to design effective ATR system, with capability of decreasing the amount of false alarm rate for images with high clutters and also, to process this developing pile of data from sensors are obviously required.

5 Recent Art of States

[1] In 2019 remote sensing Xiaoran Shi et al. [2] proposed an article. In this proposed article, super-resolution generative adversarial network (SRGAN) and deep convolutional neural network (DCNN) is utilized to eliminate poor feature characterization ability of low-resolution SAR image and to gain good generalization performance respectively. To improve the recognition accuracy and generalization performance the raw image must be pre-processed and extract the region of interest from the background which may have a characteristic that matches with target features. But image segmentation is a difficult task because of different challenges in SAR images for instance, grayscale distribution is not uniform, image brightness of the same target is uniform under different scenes and etc... To beat this problem histogram equalization is carried on SAR images to make grayscale distribute uniformly, expand the dynamic range of the pixel values, adjust the image contrast, and then select a uniform threshold for image segmentation. Acquisition of high resolution SAR images is an expensive task. In other hand poor feature characterization ability of low-resolution SAR images makes it is unable to deliver a good result in automatic target recognition and classification problems. Therefore by deeply studying about generator and discriminator, SRGAN applied to enhance low resolution images and obtained high visual resolution SAR images. On proposed article the task of DCNN is classifying the enhanced SAR images into the correct class.

[2] In 2016 IEEE Transactions Simon A. Wagner [3] proposed an article. In this proposed article, artificial training data generated by elastic distortion and affine transformations which represent examples of image errors. Using these examples the classifier trained and it should be invariant. These artificial training data incorporate prior knowledge to the classifier. Support vector machine and convolutional neural net- work combined to design an efficient ATR system. The article outlines SVM's higher generalization capability than neural networks due to their structural advantages. Because of these structural advantage the fully connected neural network replaced on the CNN by SVM for final classification. These algorithm tested on handwriting recognition and obtained good result. On these combination the task of CNN is only feature extraction (selection).

[3] In 2018 remote sensing Mengyuan Ma et al. [4] proposed an article. In this proposed article, a convolutional neutral network (CNN) model for marine target classification at patch level and an overall scheme for marine target detection in large-scale SAR images. The launch of Chinese Gaofen-3 (GF-3) satellite has provided a large number of SAR imageries, making it possible to marine targets monitoring. Eight type of marine targets (Boat, cargo ship, container ship, tanker ship, cage, iron tower, platform, and windmill) in GF-3 SAR images are labelled based on feature analysis, building the datasets for further experiments. Propose Novel CNN model called MT-CNN with six convolutional layers, three pooling layers, and two fully connected layers has been designed and capable of extracting features at different levels and achieve higher classification accuracy than existing CNN models. This paper uses average precisions (AP), which is the average of the maximum precisions at different recall values, to access the performance.

[4] In 2018 Elsevier Jian Chen et al. [7] proposed an article. In this proposed article, inspiring by the role played by convolution kernels in performance improvement develop a novel probabilistic generative model by integrating the convolution operation into statistical modeling. The proposed model called convolutional factor analysis (CFA) is more applicable to statistical recognition with small training data which make is perfect for radar automatic target recognition based on high-resolution range profile (HRRP), where sufficient training data are frequently unavailable. Compared to the traditional FA model, as a dictionary learning method the CFA model dictionary size is much smaller due to the properties of lower atom dimension and smaller atom number, also has a much lower degree of model complexity and can be learned better with limited training data compared with the traditional FA model. Each dictionary atom in our CFA model is utilized as a convolution kernel with a lower dimension and is capable of extracting the basic structure hidden in data, thus showing the potential to represent the observations with fewer dictionary atoms. In addition, owing to the conjugate property, the model parameters can be inferred via variational Bayesian (VB) algorithm, and the commutative law of convolution operation is also exploited to simplify the derivations of the posteriors. Experimental results on synthetic and measured data show that the CFA model can mine the structural information of data and have inspiring recognition performance with a small number of training samples.

[5] In 2018 remote sensing Pengfei Zhao et al. [23] proposed an article. In this proposed article, the major problem of SAR-ATR applications is its limitation of data and great variation of SAR images. The proposed model called Multi-Stream Convolutional Neural Network (MS-CNN) overcome the previously mentioned challenge by utilizing SAR images from multiple view which enables it to make full use of limited SAR image data and recognize the target classes effectively. Moreover Fourier feature fusion frame work from kernel approximation designed to disentangle the nonlinear relationship between images and classes. The full architecture is composed of four parts: a multi-stream Convolutional layer, a Fourier feature fusion layer, a fully connected layer and a softmax layer.

A multiple view SAR image of the same target is provided to the multi-stream convolution layer as input. A combined design of a multi-stream Convolutional layer and a Fourier feature fusion layer enables to filter more interacted feature from multi view image which helps to recognize the corresponding classes. What's more, it expels the leveling task by setting rational parameters, for example, the measure of the convolutional kernel and pooling, to a great extent decreasing the quantity of parameters, while making conceivable further quickening the training process. Batch normalization operation is utilized after the convolutional operation because it is essential to solve the instability problem of gradient decent in the process of backpropagation and ultimately speed up the convergence of the whole network. Rectified Linear Units (ReLUs) as the activation function for all streams of multi-stream CNN and cross-entropy used as loss function. Tensor flow 1.2 is used to implement the design on Nvidia TITAN XP GPU for training and testing the designed network.

The effectiveness of this model have been demonstrated by extensive experiments under both the Standard Operating Condition (SOC) and Extended Operating Condition (EOC) on the MSTAR dataset. The experimental results have shown that this model achieved high recognition rate.

6 Proposed Method

Image representation is basic for SAR ATR, and CNNs has been recognized as an effective and amazing tool to extract features in various tasks. Be that as it may, restricted by an absence of raw SAR image for training data, traditional CNNs is unfit to profoundly investigate the natural connection of limited SAR images, and thusly, can't enough uncover effective features in the training process of ATR process.

The proposed model named multi-stream convolutional layer, which is motivated by inherent associations of the numerous perspectives on similar target, to utilize restricted raw SAR data, and after that extract integral features from multi-view SAR images for progressively instructive SAR image representations. In addition, this technique can sufficiently extract multi view features, yet additionally to a great extent decrease the quantity of parameters and lift the training proficiency, while improving the recognition execution, which fits the SAR ATR tasks well.

In the proposed model a batch normalization operation is utilized after the convolutional operation followed by a nonlinear function called ReLU activation function. ReLU perform better without any unsupervised training for labeled SAR data and decrease the training time. The max pooling operator is utilized.

Cross-entropy cost function uses for a lose function. The formula of lose function expressed by

$$L(w,b) = -\frac{1}{C}\sum_{i=1}^{C} y_i \log \rho(y_i \mid Z^{(L)}; w,b) \tag{1}$$

7 Dataset

The MSTAR benchmark was provided by the Sandia National Laboratory SAR sensor platform. The publicly re- leased dataset is composed of 10 categories of targets, including armored personnel carrier: rocket launcher: 2S1; BMP-2, BRDM-2, BTR-70 and BTR-60; bulldozer: D7; tank: T-72, T-

62; truck: ZIL-131; air defense unit: ZSU-234. For training and testing of proposed model, the 10 classes' data shown in table 1 will be used. They were collected by an X-band SAR sensor in a 0.3 m resolution spotlight mode. SAR images for each category are shown in Figure 2. The images of ten target classes contains 2747 target chips collected with pitching angle 17° are used as a training set, while 2420 target chips with angle 15° are selected for the testing. To avoid overfitting and test model during training, images from training set are randomly chosen as the validation set.

Table 1. Detail of MSTAR dataset.

Class	Training data (17°)	Testing data (15°)
2S1	299	274
BMP-2	233	195
BRDM-2	298	274
BTR-60	256	190
BTR-70	233	196
D7	299	274
T62	299	273
T72	232	196
ZIL-131	299	274
ZSU-234	299	274
Total	2747	2420

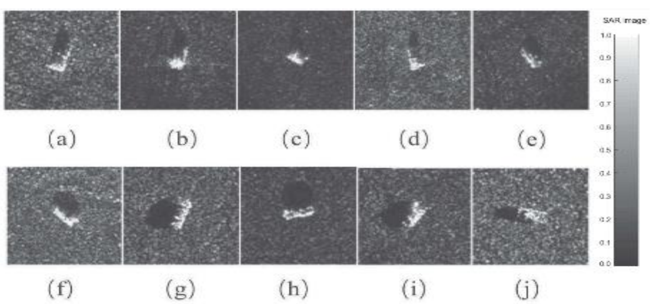

Fig. 2 SAR images for each category in MSTAR. (a) 2S1. (b) BMP-2. (c) BRDM-2. (d) BTR70. (e) BTR60. (f) D7. (g) T-72. (h) T-62. (i) ZIL-131. (j) ZSU-234 [1].

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