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Automatic target recognition and classification from synthetic aperture radar imagery using multi-stream Convolution Neural Network

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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 remotely sensed images, which belongs to a particular kind of object. The process of using a 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 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 another hand to make full use of limited SAR imagery this thesis present Multi-Stream CNN (MS-CNN) for an end to end SAR-ATR which uses multiple views of SAR images. MS-CNN takes multiple views of the same target.

Keywords*— Automatic target recognition, Multi-view CNN, Synthetic aperture radar, MSTAR, Standard operating condition, Extended operating condition*

1. INTRODUCTION

Christian Hulsmeyer of Germany was the first person who granted the license from detecting an 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 the current Day version of radar. In 1934, stuff of American Naval Research Laboratory showed the principal radar as a pulsed system, in the same year, the British were the first to utilize radar for defending against an airship assault and in 1940 the term RADAR was strike by the United States Navy as a shortening for Radio Detection and Ranging [1].

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.

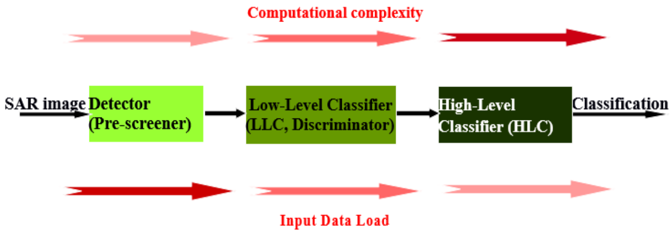

Fig. 1: General structure for an end-to-end SAR-ATR system

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 number of stages [2]. Thus, Effective Automatic Target Recognition (ATR) calculations to process this developing pile of data are obviously required.

As depicted in figure 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 a 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 is 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?[3]

Target, clutter, and noise are three terms of military roots related to 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 [4].

3. STATEMENT OF PROBLEM

A major bottleneck in military automatic target recognition is detecting or recognizing targets from imagery gathered by an imperfect sensor 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 a 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, versatile 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 that information using Automatic Target Recognition (ATR) systems to help operators to make a better decision. However, most 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 a 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 the 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 is obviously required.

5. RECENT ART OF STATES

[1] In 2019 remote sensing Xiaoran Shi et al. [5] 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. On the 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 the proposed article the task of DCNN is classifying the enhanced SAR images into the correct class.

[2] In 2016 IEEE Transactions Simon A. Wagner [6] 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 network 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 this structural advantage the fully connected neural network replaced on the CNN by SVM for final classification. These algorithms tested on handwriting recognition and obtained a good result. On this combination, the task of CNN is only feature extraction (selection).

[3] In 2018 remote sensing Mengyuan Ma et al. [7] proposed an article. In this proposed article, a convolutional neural 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 types of marine targets (Boat, cargo ship, container ship, tanker ship, cage, iron tower, platform, and windmill) in GF-3 SAR images are labeled 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. [8] 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 2019 EURASIP Journal on Advances in Signal Processing Jinwei Wan et al. [9] proposed an article. In this proposed article, devise a two-dimensional CNN model for the spectrogram feature. Moreover, by plugging a deconvolutional decoder, we coordinate the object recognition with outlier rejection task together to address HRRP (high-resolution range profile) based RATR (radar automatic target recognition) rejection problem. Batch normalization (BN) technique used in each convolution and fully connected layer to accelerate training and improve the generalization of the network.

[6] In 2018 remote sensing Zhuangzhuang Tian et al. [10] proposed an article. In this proposed article, accounts the relationship between different convolutional kernels because the absence of interdependence between convolutional kernels limits the feature extraction capacity of the convolutional layer somewhat. Devise a novel CNN named Weighted Kernel CNN (WKCNN) which integrates a weighted kernel module (WKM) into a common CNN model to improve the feature extraction capability. WKM consist of variable and activation. The variable represents the weights of the kernel and the activation used to map into (0, 1). The overall architecture of the designed CNN consists of five convolutional layers followed by max-pooling size 2 * 2 for each convolutional layer and two fully connected layers. Rectified Linear Unit (ReLU) used as an activation function for both convolutional and fully connected layers. The effectiveness of this model has been conducted under Standard Operating Condition (SOC) afterward Extended Operating Condition (EOC) on the MSTAR dataset.

[7] In 2018 Journal of Physics Linglong Tan et al. [11] proposed an article. In this proposed article, overcome the problems of image noise suppression by applying K-means and singular value decomposition (K-SVD) algorithm and prevents poor denoising. In this paper noises on SAR images will be denoised using the proposed algorithm. After the sparse dictionary introduced K-SVD algorithm is implemented by alternating the two steps of the sparse representation of the current dictionary and the updating of the dictionary using the sparse system this algorithm trains the sparse dictionary according to the representation of sparse in the dictionary. The sparse dictionary can learn from the image data. Performance evaluation results show that the proposed algorithm is effective in high dimensional data and can remove the spot noise more adequately than the complete DCT (Discrete cosine transformation) dictionary and hold the edge details better.

[8] In 2019 Elsevier Chuan Du et al. [12] proposed an article. In this proposed article, a conditional generative model for radar high resolution range profile (HRRP) target recognition named Discriminative Conditional Variational Auto-Encoder VAE (DCVAE) adopted to learn the discriminative representations and sufficiently encode the observed feature variability by taking the multi-layer perception (MLP) as the sufficient statistics of posterior approximation distribution, thus offering the potential to improve the overall recognition performance. The model consists of two models, a generative model and an inference model Gaussian distribution is used to model the amplitudes of pre-processed average profiles and introduce a Gaussian latent variable z to describe the underlying features.

6. PROPOSED METHOD

Image representation is basic for SAR ATR, and CNN's 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 [13]. In addition, this technique can sufficiently extract multi-view features, yet additionally, to a great extent decrease the number 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 performs better without any unsupervised training for labeled SAR data and decreases the training time. The max-pooling operator is utilized.

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

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

7. DATASET

The MSTAR benchmark was provided by the Sandia National Laboratory SAR sensor platform [14]. The publicly released 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 the 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 often target classes contain 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 the 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

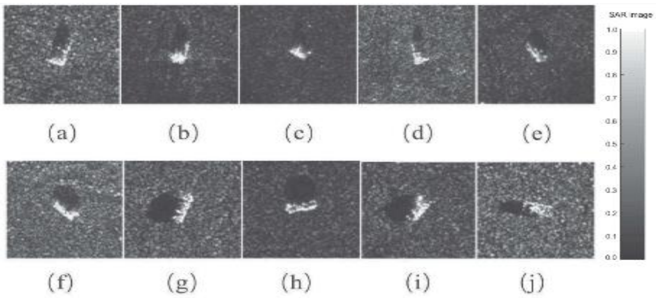

Fig. 2 SAR images for each category in MSTAR. (a) 2S1. (b) BMP-2. (c) BRDM-2. (d) BTR70. (e) BTR60. (f) D7. (g) T-72. (h) T-62. (i) ZIL-131. (j) ZSU-234 [14].

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