ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Vol 8, Issue 5, May 2021

Synthetic Aperture Radar Feature extraction and Emerging Trends

[1] SK Wagle, [2] Dr A Bazil Raj, [3] Dr KP Ray
[1][2][3] Defence Institute of Advanced Technology, Pune, India

Abstract: Synthetic Aperture Radar (SAR) image analysis and classification is one of the challenging as well as promising field in Modern Military warfare in reducing the reaction time between the Sensor and the shooter grid. Towards this, many attempts have been made for Automatic Target Recognition using various Machine learning and Deep learning Techniques. In this Paper, an attempt is made to study the existing techniques used to classify various SAR images without human intervention. The complexity involved in SAR images is more, mainly due to lack of sufficient training images to train the Deep Learning Neural Network Model. This may lead to Overfitting, due to which the Model may work with the Training images only but may not work with the testing images. To mitigate this issue of overfitting, we have suggested Data Augmentation. Certain Data Augmentation techniques have been compared and a simplistic model is suggested by which, we can achieve a high degree of accuracy in Military Target prediction with the limited amount of Training images.

Index Terms— AI, Data Augmentation, Deep Learning, Synthetic Aperture Radar (SAR).

I. INTRODUCTION

Human beings can easily identify all the objects in the image, their position and the various interactions between them. Deep learning, computer vision, etc try mimic this unique human skill which has been generated through years of evolutionary process by using multiple layers of Convolution Neural Networks in which each layer tries to extract some typical features from the object. But in order to train the model, you require to provide a very large number of training samples so that the model tries to reduce its prediction error.

In case of a Synthetic Aperture radar image, the images are generated by a SAR satellite or an aircraft. These images are very few in number and thus due to lack of sufficient training samples, the model is unable to predict the targets to the desired accuracy. This leads to manual image detection, which is very strenuous, time consuming and difficult for a very large amount of data received with limited training samples. This especially is very crucial in case of Military targets, where the time of response between the Sensor grid to Decision Making and further communication it to the Shooter Grid is very crucial.

The present paper attempts to build a Deep learning Model using various data Pre-processing techniques to overcome the short coming of less images by modifying the existing images using Data Augmentation techniques.

Deep Learning concepts

Deep learning is a part of Artificial Intelligence which has emerged as the fastest growing research area and sees applications in a variety of fields like Image Processing, Self driving cars, cancer and Tumor detection, diabetic Neuropathy and various medical diagnosis, Voice search and analysis, Robotics and automation, Business and Data Analytics, Facial recognition and security, Natural Language Processing and a large number of Military Application.

A Neural Network tries to mimic the way brain understands to recognise objects and to identify them. A neural network consists of interconnected groups of nodes,

Similar to the Neuron Structure of the brain. Each group of nodes corresponds to a layer. A "deep" neural network has multiple such layers, each layer having Multiple Nodes. Each layer tries to extract some unique feature from the image. In case of Supervised learning, the Model tries to learn the object based on the labelled images provided as training set while training the Model. The Neural Network Model uses Stochastic Gradient descend and Back Propagation Models to reduce the error and keep improving the accuracy using Multiple Rounds also called epochs. There are three main types of Supervised Learning Models namely the Artificial Neural Networks (ANN), the Convolution Neural Networks (CNN) and the

ISSN (Online) 2394-2320

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Vol 8, Issue 5, May 2021

Recurrent Neural Networks (RNN). Each Models have multiple variants however the CNN models are best suited for Image applications such as Synthetic Aperture Radar SAR image classification.

.

SAR and MSTAR data sets

Many attempts have been made to automatically detect Moving targets from various satellite images including the SAR images. This is known as Automatic Target Recognition (ATR). Humans cannot naturally observe parts of the electromagnetic spectrum beyond the visible band. Radar can also be used to determine the composition of an object by analysing how the waves react to the object. Andrew Profetaa *etal*. brought out in [1] various ways in applying ATR for SAR images. In [2] Yihua Lan showed feature learning and multilayer network in the interpretation of Polarimetric synthetic aperture radar (PolSAR) image, a classification algorithm based on deep convolutional neural network is proposed, and is used for PolSAR image classification. He compared various feature extraction and classifiers used in serial and parallel combinations.

The ATR can be applied especially for Military Targets where Satellites/ Radars/ Early Warning Airborne Radars/ drones can be utilised to capture the SAR image and using ATR to identify the object and pass this information to the Shooter Grid on a real time basis.

The Moving and Stationary Target Acquisition and Recognition (MSTAR) program was developed to provide a dataset that would facilitate the development of an accurate and robust ATR algorithm able to perform identification and classification of targets in air to ground SAR imagery. The program gathered data from 1995 to 2001. The program consisted of four data collects with variable operating conditions. There were variable sensing conditions, environments, and targets.

Overview of existing models for sar target recognition

As compared to the previous Machine Learning approaches, the deep learning approaches using multi layered CNN was able to offer better performance. In this case in place of using various filters for feature extraction from the images, the deep learning approach, wherein the filters are auto defined by the Model itself.

In 2015, David A. E. Morgan in [3] proposed a deep CNN network, where in he showed that a simple deep learning Model, without any specific effort to fine tune the network topology, optimisation parameters, or selectively choose the most successful instance of the trained model on this data set. The Prediction accuracy obtained was 92.3 percent. Furthermore, this study suggests that a trained classifier using the CNN approach could be adapted relatively quickly to incorporate new, previously unseen targets. This can be compared with the results obtained from other methods. For example O'Sullivan *etal* [4] reported a prediction accuracy of 95.05% successful classification rate for the same 128X128 problem under similar conditions using the Conditionally Gaussian model technique. The results achieved by Srinivas *etal* [5] suggest a similar but slightly lower classification rate 92.8% for this method. The various other classification methods widely used are Support Vector Machines (SVM). Zhao *etal* [6] showed SVM results in prediction accuracy of around 90.1% while Sun *etal*. [7] showed an accuracy of 92,7 percent for the technique Adaptive Boosting in ATR.

Yunyan Wang [8] compared various classification techniques and categorised them into three types in which, the first category, the input image is fed to general classifier, such as 'sift' or 'Hog' followed by a SVM classifier. The second category he compared was in which, the feature and classifier are learned together in a black box at the same time, such as CNN network. The third category was of classifiers in which the feature extraction and classifier are learned separately, feature extraction network is trained by a separate image data set of target image, while the classifier is trained by another data set as proposed by Maxime Oquab *etal* [9]. This kind of classification model not only makes full use of the benefits of feature learning, but also overcomes requirements for the number of training data. In [10] Michael Wilmanski *etal* brought out that with a combination of good initialization and effective stochastic gradient decent modifications, nearly 98% correct classification can be achieved on the MSTAR test set using only the training set for learning

In [11] Mohammad Rostami, ***etal*.,** addressed the problem of SAR image classification when only a few labelled data were available. The problem was resolved as a semi-supervised learning. It was based on transfer

ISSN (Online) 2394-2320

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Vol 8, Issue 5, May 2021

learning from electro-optical data to SAR data. It is relatively easy to to generate labelled data in EO images. The classification models were two deep convolutional neural networks that shared their fully-connected layers. The networks were trained such that the convolutional layers served as two deep encoders that matched the distributions of the two EO and SAR domains.

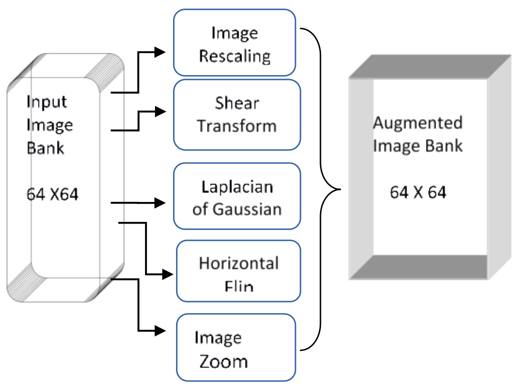

Fig 1 Data Augmentation

Increasing accuracy with data augmentation

In [12], Hidetoshi *etal*,2017, used the properties of Alexnet for Data Augmentation, where in they trained the CNN once with and next without data augmentation. During Data Augmentation, they trained the CNN with a randomly cropped images of the 100 X 100 pixel image, whereas when model was trained without augmentation, fixed cropped images of 96X96 pixels was used. The classification accuracy increased from 98.75 percent to 99.56 percent using data Augmentation. In [13], JUNYA LV has shown a data augmentation algorithm using target reconstruction based on attributed scattering centers (ASC). The ASCs reflect the electromagnetic phenomenon of SAR targets, which can be used to reconstruct the target's characteristics. The sparse representation (SR) algorithm is first employed to extract the ASCs from a single SAR image. Afterwards, some of the extracted ASCs are selected to reconstruct the target's image. By repeating the process, many new images can be generated as available training samples. The data augmentation proposed to be used in the algorithm is shown in Fig 1. In order to deal with the limited number of trainable images, in case of SAR images, it is proposed to use certain image pre-processing techniques like image re scaling, Laplacian of Gaussian, image shearing, Zoom range and horizontal flip. This will largely prevent the problem of Over fitting and significantly improve the prediction accuracy.

Limitations of existing Models

In most of the real-world image classification, a large amount training data is available and hence a very deep model is required to attain the required prediction accuracy. Jun Ding *etal* [14] has compared Models as deep as 22 Layers have been used for better accuracy. However, in case of SAR data, a very limited number of images are available and hence very deep models may not fetch any additional input but will be very computationally expensive. Here, we propose a simplified Model without building a multi layered CNN like the Le Net and Res net etc.

PROPOSED MODEL AND ALGORITHM

A simplified Model is proposed which will reduce the Computational time and complexity at the same time

Layer Type	Image Size	Feature Maps	Kernel Size
Input Layer	64X64	1	
Convolutional	62X62	32	3X3
Max Pooling	31X31	32	2X2
Convolutional	29X29	32	3X3
Max Pooling	15X15	32	2X2
Convolutional	13X13	64	3X3
Fully Connected	1	3136	-
Output	1	2	-

Fig 2 Proposed Model parameters

enhance the prediction accuracy. The Model parameters of the deep learning model are given in Fig 2. It gives the details of the image size, the number of feature maps and the kernel size used at each layer to do the convolution operation. The T 72 and BMP tank images from MSTAR data set are separated into training sets and data validation sets in the ratio 80:20. Further Data Augmentation is used to generate augmented images to avoid over fitting. The Augmented images are fed to a deep Learning Feature extractor having 3 alternate layers of Convolution and Max Pooling. This is followed by Fully connected layer

ISSN (Online) 2394-2320

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Vol 8, Issue 5, May 2021

which is then connected to a Sigmoid Classifier as shown in Fig 3.

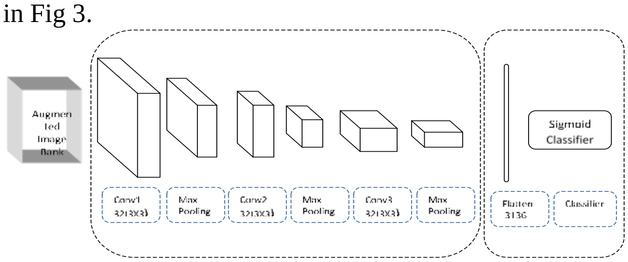

Fig 3. Proposed Model

Experimental Results

The software libraries used were Python, Tensorflow Keras and Theano. The Platform used was Anaconda on Linux Ubuntu and the IDE was SPYDER. The Adam Optimizer was used Stochastic Gradient descend and Binary Cross Entropy was used for calculating the loss function. A total of 10 Epoch were used to get an accuracy of 98.83 percent for the training set and an accuracy of 98.62 percent for the test set. The results were quite promising for the limited image bank available for SAR images. The over-fitting problem was resolved. The Number of Epochs were increased to 15 gradually, but there was no significant increase beyond 10 Epochs. Similarly, four Convolution Layers were attempted, however the accuracy reduced marginally and hence3 Convolution layers were felt as optimal.

Conclusion and future work

It was seen that by using simple techniques like data augmentation, a simplified Deep learning Model can be used for SAR image classification. This has a great impact in reducing the Sensor to Shooter Grid in Military Combat by reducing the Time drastically between Target Identification and Quick engagement of Target. The Present Experiment was only dealing with T 72 and BMP tanks classification. The same algorithm can be extended to Multiple SAR Target identifications, especially when the number of SAR images of Military targets are limited.

REFERENCES

[1] Convolutional Neural Networks for Synthetic Aperture Radar Classification. Andrew Profetaa, Andres Rodrigueza,b and H. Scott Clouse, 2016

[2] PolSAR Image Classification Based on Deep Convolutional Neural Network Yihua Lan, High-efficiency Utilization of Solar Energy, Hubei

[3] Deep convolutional neural networks for ATR from SAR Imagery David A. E. Morgan, BAE Systems, University of Technology, Wuhan 430068, China 2015

[4] O'Sullivan, J., DeVore, M., Kedia, V., and Miller, M., \Sar atr performance using a conditionally Gaussian model," Aerospace and Electronic Systems, IEEE Transactions on 37, 91{108 (Jan 2001).

[5] Srinivas, U., Monga, V., and Raj, R., \Sar automatic target recognition using discriminative graphical models," Aerospace and Electronic Systems, IEEE Transactions on 50, 591{606 (January 2014).

[6] Zhao, Q. and Principe, J., \Support vector machines for SAR automatic target recognition," Aerospace and Electronic Systems, IEEE Transactions on 37, 643{654 (Apr 2001).

[7] Sun, Y., Liu, Z., Todorovic, S., and Li, J., \Adaptive boosting for SAR automatic target recognition," Aerospace and Electronic Systems, IEEE Transactions on 43, 112{125 (January 2007).

[8] PolSAR Image Classification Based on Deep Convolutional Neural Network. Yunyan Wang . High-efficiency Utilization of Solar Energy, Hubei University of Technology, Wuhan 430068, China(2015)

[9]. Maxime Oquab, Leon Bottou, Ivan Laptev, Josef Sivic (2014) Learning and Transferring Mid-Level Image Representations using Convolutional Neural NetWorks. IEEE Conference on Computer Vision and Pattern Recogintion

[10] Modern Approaches in Deep Learning for SAR ATR ,Michael Wilmanski, Chris Kreucher and Jim Lauer, Integrity Applications Incorporated, Ann Arbor MI, 48108, 2016

[11] Deep Transfer Learning for Few-Shot SAR Image Classification
Mohammad Rostami, Soheil Kolouri, Eric Eaton and Kyungnam Kim, Remote sensing Journal June 2019

[12] Deep Learning for Target Classification from SAR Imagery Data Augmentation and Translation Invariance. Hidetoshi FURUKAWA 2017

[13] Data Augmentation Based on Attributed Scattering Centers to Train Robust
CNN for SAR ATR JUNYA LV , AND YUE LIU IEEE access VOLUME 7, 2019

[14] Convolutional Neural Network With Data Augmentation for SAR Target Recognition Jun Ding, Bo Chen, Member, IEEE, Hongwei Liu, Member, IEEE, and Mengyuan Huang, 2016

