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A Feasibility Analysis of the Use of ISAR Training Data in Machine Learning-Based SAR ATR

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Abstract
Processing of synthetic aperture radar (SAR) images for automatic target recognition (ATR) is a critical application especially in military surveillance. In particular, numerous machine learning-based SAR ATR methods have been proposed for this task. However, data training and testing stages of all these methods are based on the exploitation of SAR signatures of the target under investigation. Considering the high variability of radar targets, obtaining such signature data is obviously a costly and time consuming process. In this study, therefore, a feasibility analysis of the use of inverse-SAR (ISAR) training data in SAR ATR has been made for the first time. The turntable ISAR and circular SAR images of three different vehicles are used in training and testing is performed by means of SAR images of three similar targets within the publicly available MSTAR dataset. Also, three most prominent machine learning methods, namely KNN, SVM and ANN are used in conjunction with three different feature extraction algorithms namely, GLRLM, GLSZM and GLCM. The obtained results reveal that the GLCM+ANN algorithm pair is the most effective model with 85% accuracy.

Key Words
"Automatic Target Recognition, Synthetic Aperture Radar, Inverse Synthetic Aperture Radar, Artificial Intelligence"

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1. Introduction

Synthetic aperture radar (SAR) and inverse-SAR (ISAR) are highly effective microwave remote sensing techniques that can produce high resolution images of ground and air targets (Vertiy et al., 2011). In SAR, the radar platform at some height moves along a straight path while taking the images of the fixed or moving targets on the ground from a certain point of view. Contrarily, in ISAR, the radar platform is fixed and the images of airborne targets are generated via the motion of targets in a certain angle of view (Yiğit, 2020). In addition to imaging of airborne targets, the ISAR technique has also been used in imaging of ground targets mounted on a turntable with 360-degree rotation capability (Blacknell and Vignaud, 2013). In this mode, termed as turntable or ground-based ISAR, reflectivity and scattering mechanism information about targets can be more feasibly achieved in a controlled environment.

An important application of SAR imaging is the detection and identification of military vehicles on the ground. The images generated by SAR systems have been extensively used for the purpose of automatic target recognition (ATR). Specifically, numerous machine learning-based SAR ATR methods have been proposed for this task (Özkaya, 2020; Liu and Li, 2013). This application, however, involves challenges and requires reference image signatures for a typical range of target types and data collection parameters. Many studies have been carried out to recognize the targets from the images obtained by processing the signals obtained from the scanned region in the SAR technique (Blacknell and Vignaud, 2013; Özkaya, 2020; Dong et al., 2017; Miao and Liu, 2021). In almost all of these studies, the test and training set needs to exploit SAR reference data acquired with the identical measurement technique. Noting that obtaining SAR images of all possible targets from all possible perspectives is both a costly and time-consuming process, such studies usually face with limited data problem and thereby resulting in a poor performance. Alternatively, with ground-based ISAR imaging, target scattering parameters and images can be gathered in a very practical, fast and inexpensive way. Thus, training sets trained with these data can be used for target detection in real SAR images. To our knowledge, no machine learning-based studies have been conducted to detect targets in SAR images by means of ISAR signatures (Cui et al., 2023; Song et al., 2023; Demirci & Izumi, 2023).

In this study, therefore, ATR were tried to be carried out from real SAR images by using ground-based ISAR images (Özkaya, 2020; Copsey, 2004; Demirci et al., 2015; Blacknell and Vignaud, 2013) and a database trained with popular artificial intelligence algorithms such as Artificial Neural Networks (ANN) (Duysak et al., 2020), k-nearest neighbor (KNN) (Duysak and Yiğit, 2019) and Support Vector Machine (SVM) (Özkaya, 2020). The features of 2D SAR and ISAR images were extracted with Co-occurrence Matrix (GLCM), Gray Level Run Length Matrix (GLRLM) and Gray Level Size Zone Matrix (GLSZM) methods, and the performances of artificial intelligence algorithms and feature extraction techniques were tested. While SAR images of 3 different targets in the MSTAR (Novak et al., 1998; Liu and Li, 2013; Miao and Liu, 2021; Martone et al., 2009; Novak et al., 1993; Dong et al., 2015) dataset were used as test data, 3 different ISAR images were used as training data. The work is organized as follows. In the second section, while the test and training data are presented in detail, the feature extraction and artificial intelligence algorithms are briefly introduced. In the third section, the obtained results are presented comparatively and the article is summarized in the conclusion section.

2. Materials and Method

2.1. Definition of the Dataset

As test data, we make use of the MSTAR dataset provided by the Defense Advanced Research Projects Agency (DARPA) and the American Air Force Research Laboratory (AFRL) (MSTAR Public Targets, 2021) The collection contains X-band SAR imagery of numerous vehicles collected at depression angles in the range [15°,45°] with 1° azimuth bandwidths over the full aperture. From this large dataset, 3 ground vehicles, labeled as T72, D7 and T62 were selected as representative target samples. Noting that the SAR signatures exhibit strong fluctuations as the target aspect varies, 280 images of each target, with a total number of 840 images, acquired at different observation angles were utilized. The left column of Figure 1 shows these targets and their sample SAR images.

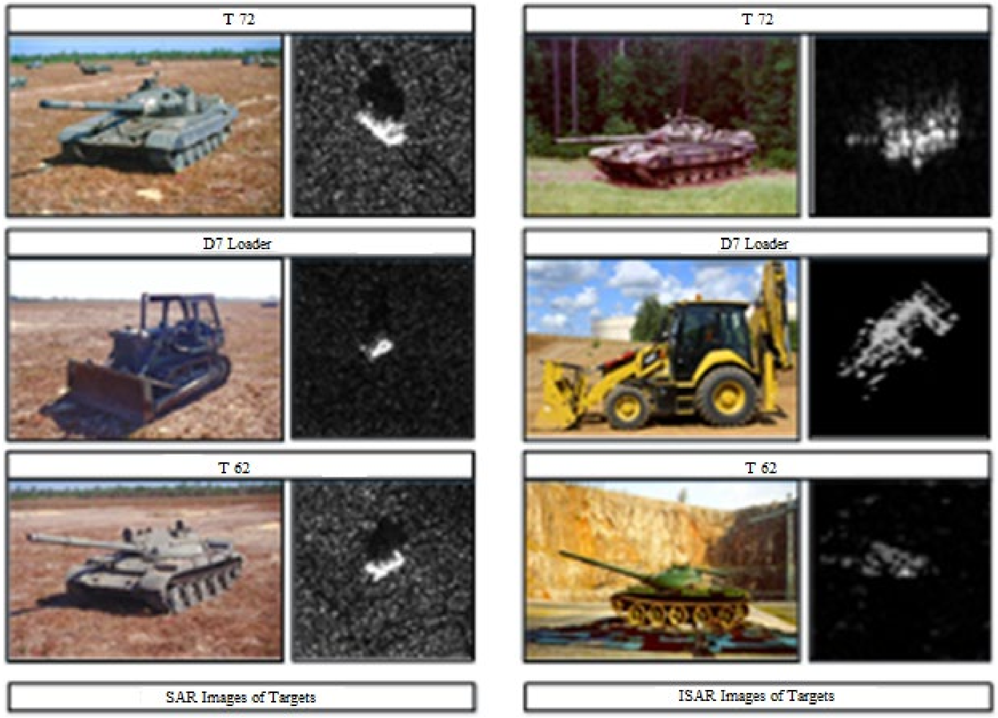

Figure 1. Targets and their sample radar images used in the proposed machine-learning based SAR ATR. SAR images as the test data (left), turntable ISAR/circular SAR images as the training data (right)

As for training data, the turntable ISAR and circular SAR image data of 3 targets were employed. The targets were selected to be similar to those used in testing, as can be seen in the right column of Figure 2. The dataset for the first target is the X-band turntable ISAR response of a T72 tank acquired for the depression angles in the range [27.9°,31.9°] and 3.9° angular spans of the full azimuth coverage. The raw dataset was collected by Georgia Tech Research Institute (GTRI) and can be accessed via Air Force Research Laboratory (AFRL) website (GTRI dataset, 1997). We selected representative samples of angular data and applied image preprocessing (i.e., windowing, zero-padding and clutter removal) and reconstruction techniques to obtain ISAR image samples to be used in training. The second dataset is the airborne circular SAR images of a backhoe loader and referred to as the "GOTCHA Volumetric SAR Data Set, Version 1.0" (Gotcha Volumetric SAR Data Set Overvie, 2021). It contains X-band spotlight SAR images collected with full rotation and at 8 different incidence angles ranging from 43.7° to 45°. Lastly, the third dataset is the turntable ISAR images of a main battle tank corresponding to a depression angle of 10° as presented in (Copsey, 2004) For the 2nd and 3rd targets, we reproduced the published ISAR images of the targets through image rotation, On the whole, a total of 255 training images with 85 images for each target were deployed in our analysis.

2.2. Proposed Framework

The SAR ATR framework proposed in this study is illustrated in Figure 2. As mentioned, the framework is based on the use of ISAR imagery as training data.

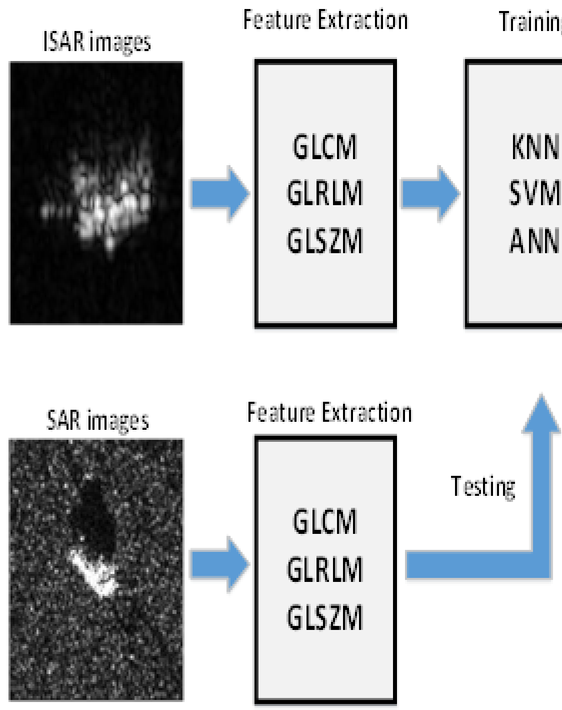

Figure 2. Proposed Framework

In addition, the framework is distinct in that three popular feature extraction algorithms, called GLCM, GLRLM and GLSZM are tried in conjunction with 3 popular artificial intelligence algorithms, namely KNN, SVM and ANN. These algorithms are applied to SAR test data and ISAR training data in pair-wise combination. The ATR performance results can then be compared with each other to determine the best algorithm pair. The employed artificial intelligence algorithms are briefly explained in the following.The KNN algorithm is one of the most basic and simple learning algorithms (Yigit, 2018). The working system uses the multidimensional feature space created from the given KNN, which is quite simple. It defines the test object according to the nearest neighbor value in the measurement space. The distance between objects is usually determined by the Euclidean length, and the output of the algorithm is evaluated according to the results of different degrees of neighborhood.

The SVM algorithm is a very effective classifier for linear and nonlinear problems (Duysak et al., 2020). Unlike KNN, using kernel functions, a suitable decision surface and a separation hyperplane with the maximum distance to the nearest points of the training set are determined. Classification or regression is provided according to this kernel function.

ANN[21], on the other hand, is a system that consists of many processing units that are heavily interconnected, receive signals from other neurons, combine them, transform them, and produce a numerical result. In the most general terms, the processing units correspond to real neurons and thus this structure constitutes the ANN. All parameters of 3 different AI techniques used in this study are given in Table 1.

Table 1. The Parameters of the AI Techniques

Model	Parameters	Set type/Value
KNN	Distance Function	Euclidean
	K neighborhood number	1
SVM	Kernel Function	Radial Basis
	Kernel Function coefficient	1
	Slack variable coefficient (C)	100000
ANN	Epochs	300
	Learning rate	0.4
	Momentum parameter	0.2
	Learning algorithm	Levenberg-Marquardt
	Hidden layer	2

Six different classification criteria were used to evaluate the performance of the proposed models. These metrics are Specificity (SPE), Precision (SEN), Accuracy (ACC), F1-Score, Matthews Correlation Coefficient (MCC). Equations for all these metrics are given below.

$$Accuracy = (TP + TN) / (TP + FN + TN + FP) \quad (1)$$

$$Sensitivity = TP / (TP + FN) \quad (2)$$

$$Specificity = TN / (TN + FP) \quad (3)$$

$$Precision = TP / (TP + FP) \quad (4)$$

$$F1 - Score = (2 \times TP) / (2 \times TP + FN + FP) \quad (5)$$

$$MCC = \frac{\mathrm{TP} \times \mathrm{TN} - \mathrm{FP} \times \mathrm{FN}}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (6)$$

Where TP is True Positive, TN is True Negative, FP is False Positive and FN is False Negative. Metric performances of the proposed methods are given in Table 2.

Table 2. Performance of Proposed Frameworks.

Methods	**Evaluation Metrics (%)**					
	SEN	SPE	ACC	PRE	F1-Score	MCC
GLCM+KNN	58.04	79.02	58.85	81.90	56.96	49.23
GLCM+SVM	61.57	80.78	62.31	82.62	61.25	53.36
GLCM+ANN	79.12	89.33	84.05	76.07	75.49	65.53
GLRLM+KNN	45.88	72.94	46.92	79.82	39.71	33.32
GLRLM+SVM	49.80	74.90	50.77	80.43	45.66	38.84
GLRLM+ANN	51.76	75.88	52.69	80.75	48.41	41.38
GLSZM+KNN	52.94	76.47	53.85	80.95	50.09	42.92
GLSZM+SVM	54.51	77.25	55.38	81.21	52.21	44.88
GLSZM+ANN	56.08	78.04	56.92	82.25	54.27	46.80

3. Results

The criteria obtained as a result of three different proposed feature extraction algorithms and three different popular AI techniques are given in Table 2. As seen in the table, the best values were obtained in the GLCM+ANN technique. When the feature extraction techniques are examined among themselves, it is clearly seen that GLCM is superior to the others. The confusion matrix of the proposed method is given in Figure 3.

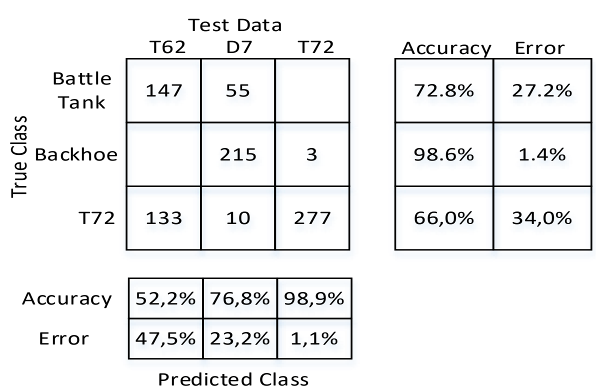

Figure 3. Confusion Matrix

4. Discussion

When the confusion matrix is evaluated, it is seen that the T72 tank was detected with an accuracy of 98.9%. The most important reason for this is the use of images belonging to the same target in both training and testing. In addition, the training data of the T72 tank are ISAR images obtained from different angles. However, ISAR images of other targets were obtained from the literature and the number of images was increased by the rotation method. Therefore, the classification accuracy of other targets was low. On the other hand, the D7 target (which is loader) in the MSTAR data was classified as Backhoe with 76% accuracy, and this result provided information about what the target was. In MSTAR, the T62 tank was detected in the confisin matrix with an accuracy of approximately 52%, as it was similar to the Battle tank and T72 tank in the training data. Among the SAR images of the T72, 280 images of the T62 tank are classified as 147 Battle Tanks and 133 as T72 tanks, and the failure to assign any images of the backhoe target reveals that this target is a tank with a high probability. Since the D7 target is a bucket, 215 of the 280 SAR images are assigned to the Backhoe model loader and the remaining images are assigned to the battle tank and T72 tank, indicating that this target is a loader with 76.8% accuracy. These results revealed that even targets that have never been trained can be predicted with appropriate methods.

5. Conclusion

In this study, for the first time, classification of SAR images was performed using a dataset trained with ISAR images. Three different ISAR images were used as training data. Among these targets, 85 different ISAR images of the T72 tank were obtained from the MSTAR data, while the images of the other two targets (Backhoe Loader and Battle Tank) were taken from the publications in the literature. Only one ISAR image of the Backhoe loader and battle tanks was reproduced using the rotation technique, resulting in 85 different images. Thus, a total of 255 images of the three targets were used in the training. MSAT SAR data of 3 targets were used for testing purposes. Only one of these targets (T72) consists of SAR images of the same target as the target in the training data. The other two targets consist of images that have never been used in education but are similar to educational targets. In this way, ATR performance with test targets that were never trained was examined. For classification, 3 different feature extraction algorithms, namely GLRLM, GLSZM and GLCM, were applied and the data was trained with KNN, SVM and ANN. The results shows that the best performance was obtained with the combination of GLCM+ANN with an accuracy of 84.05%. When the confusion matrix is evaluated, almost all of the T72 tank is assigned as T72 tank, T62 images are distributed between the two tanks in the training data, and the images of D7 loader are assigned to the backhoe loader with a rate of 76.8%, revealing that even the images that have never been trained can be recognized with the appropriate model and classification.

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