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Classification Of Non-Fluctuating Complex Targets Using Modwpt Feature Extraction

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Abstract:

The classification of complex targets is one of the challenging tasks in the radar research field. The Radar Cross-Section is the prime attribute for the target classification. The RCS of the complex targets is an amalgamation of various complicated shapes where computational electromagnetic approaches require tremendous computations. A dedicated approach for modelling the complex targets with simple scatters like a sphere, circular cylinder, frustum, and circular disc are developed. The developed model features are extracted using the MODWPT extraction method and are given to different classifiers specifically SVM, k-NN, and ANN. The classification of the non-fluctuating complex targets by the classifier of the highest accuracy is determined.

Index Terms: Target Classification, Complex Targets, RCS, MODWPT, Relative Wavelet Energy, SVM, k-NN, and ANN.

I. INTRODUCTION

In the field of modern radar systems, classification of targets is one of the main research interests [1]. The recent advancements in technology developed many algorithms for the classification of radar targets. The RCS classification of objects plays a main role in the design of radar systems to classify the objects and mainly used for the stealth analysis in the military and civil applications. The RCS of the simple objects of elementary profiles are calculated using analytical methods like Geometry optics (GO) and Physical optics (PO). Since all the natural targets like aircrafts, ships are complex targets it is difficult to apply these analytical techniques for predictions. Earlier many methods like Matrix Pencil method using Singularity expansion method (SEM) have been used [2]. All these methods are applied to the late time part of the signal and are independent on the aspect angle and polarization of the signal or excitation source. Also, there methods are found to be inconvenient for real time applications. Frequency dependent methods have been developed and the time-frequency characteristics of the signals are observed using the wavelet transforms.To enhance the accuracy of the complex target detection various computational electromagnetic approaches have been developed. These computational electromagnetic approaches require a lot of computations and become cumbersome for real-time targets. So a dedicated machine learning model is used to develop the complex targets. For complex objects, the experimental or numerical computation methods like Method of moments (MoM) or Finite element analysis (FEM) are used. The complex targets are realized as an independent combination of simple geometrical structures like a sphere, circular cylinder, frustum, and circular disc.The classification performance is improved by extracting features from the original signal of the radar echoes. Maximal overlap discrete wavelet packet transform (MODWPT) feature extraction is used. Classification of simple targets using the MODWPT feature extraction is found to be effective and the same feature extraction method has been applied for the complex target classification.The machine learning classification models namely Support vector machine (SVM), k-nearest neighbor (k-NN), and artificial neural networks (ANN) are developed. By tuning various model parameters, the classification of the targets with significant accuracy is observed.

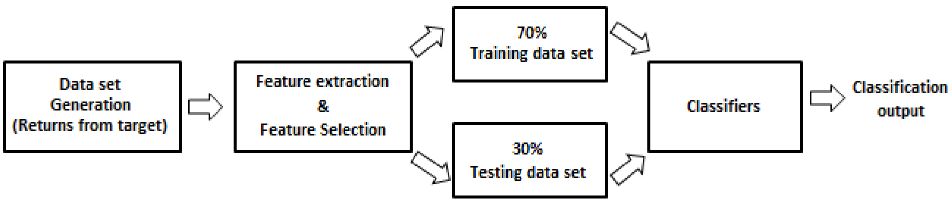


Fig. 1: Block diagram of non-fluctuating complex targets classification.

The process of the experimental study on the classification of non-fluctuating complex targets is carried as shown in the block diagram.The organization of the rest of the paper is as follows. Section 2 describes the data set of the targets with a different geometrical shape and variation in RCS as well as their properties and development of the complex target models. Section 3 explains the proposed MODWPT feature extraction method and Entropy-based feature selection. The classification models are described in section 4 whereas section 5 presents the experimental results followed by conclusions in section 6.

II. DATASET

RCS is the ability of the target to reflect the incident radar signal on it in the direction of the radar [3]. It is the measurement of size of target as seen by the radar and also contains the characteristics of particular target.

$$\sigma = \frac{\text{Power reradiated towards source per unit solid angle}}{\text{incident power density}/4\pi}\,\mathrm{m}^2 \qquad (1)$$

The RCS is a function of various parameters like frequency, polarization, target configuration and orientation with respect to incident field. For complex targets, RCS is highly dependent on the aspect angle.

Due to a large variation in the RCS pattern from one aspect angle to other, RCS is displayed in the logarithmic form for convenience.

$$\mathrm{RCS(dBsm)} = 10\log_{10}\sigma \tag{2}$$

A. Complex target modeling

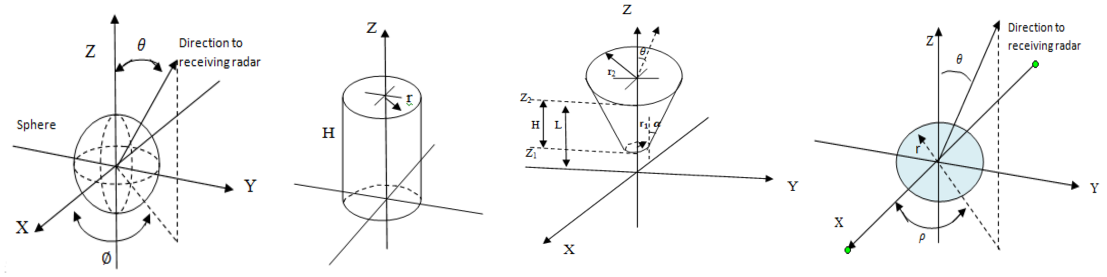
The RCS of complex targets developed with a combination of simple geometric shapes can be analyzed using analytic methods. To accurately predict the RCS pattern of complex targets with more complicated shapes and materials, the computational electromagnetic approaches like Method of Moments (MoM), Finite element analysis (FEM) or Fast multi-pole method(FMM) are used.The RCS of the simple canonical targets namely sphere, circular cylinder, frustum, and circular disc are mentioned below:

Region	**RCS of sphere**
Optical	$\sigma = \pi r^2 \quad r \gg \lambda$
Rayleigh	$\sigma = 9\pi r^2 (kr)^4 \quad r \ll \lambda$
Mie	$\frac{\sigma}{\pi r^2} = (\frac{j}{kr})\sum_{n=1}^{\infty}(-1)^n(2n+1)[\left(\frac{krJ_{n-1}(kr) - nJ_n(kr)}{krH_{n-1}^{(1)}(kr) - nH_n^{(1)}(kr)}\right) - (\frac{J_n(kr)}{H_n^{(1)}(kr)})]$

Here $k = \frac{2\pi}{\lambda}$ and $H_n^{(1)}$ is the Hankel function of order n, $H_n^{(1)}$=$J_n(kr) + jY_n(kr)$ and Y_n is the spherical Bessel function of second order.

Shape	RCS for normal backscattered incidence	RCS for non-normal backscattered incidence
Circular cylinder	$\sigma_{\theta_n} = \frac{2\pi H^2 r}{\lambda}$	$\sigma = \frac{\lambda r\sin\theta}{8\pi(\cos\theta)^2}$
Frustum	$\sigma_{\theta_n} = \frac{8\pi\left(z_2^{\frac{3}{2}} - z_1^{\frac{3}{2}}\right)^2}{9\lambda}\frac{\sin\alpha}{(\cos\alpha)^4}$	$\sigma = \frac{\lambda z\tan\alpha}{8\pi\sin\theta}(\tan(\theta-\alpha))^2$
Disc	$\sigma_{\theta_n} = \frac{4\pi^3 r^4}{\lambda^2} \quad (\theta = 0°)$	$\sigma = \frac{\lambda r}{8\pi\sin\theta(\tan\theta)^2}$

cone angle, $\tan\alpha = \frac{r_2 - r_1}{H}$



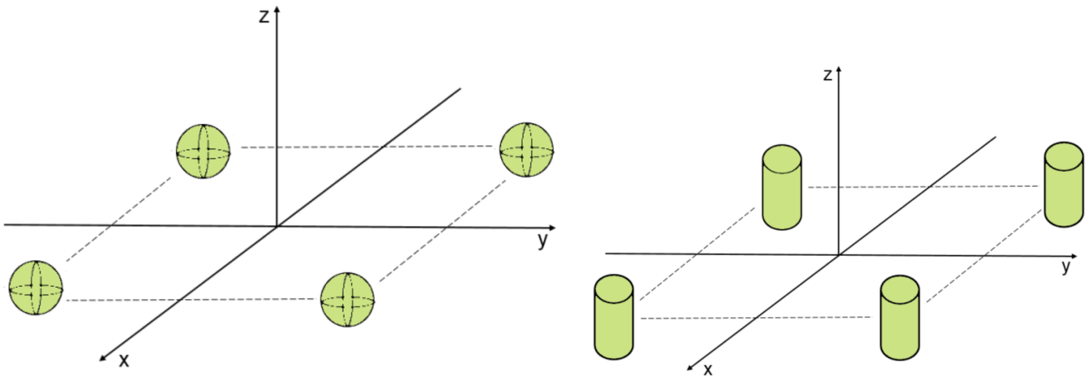
(a) (b) (c) (d)

Fig. 2: (a) sphere. (b) circular cylinder. (c) frustum. (d) circular flat plate (disc).

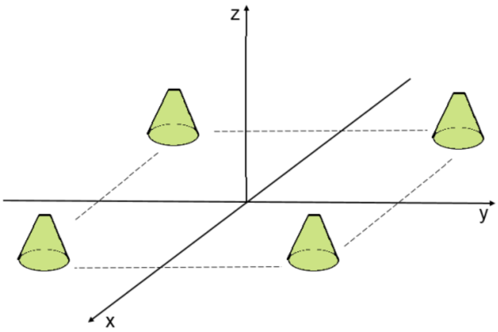
As the computational electromagnetic approaches require a significant number of computations, an alternative approach is developed.Complex targets are realized from the independent simple geometric shapes as a combination of simple scatters. The modelling of complex targets using four scatters is developed [4]. The scatters are located at the four vertices of a square. Without loss of generality, the square is placed in the xy plane. Complex targets namely complex sphere, complex cylinder, complex frustum, and complex disc are modeled. Thereby, the RCS pattern of the complex targets is a coherence of all simple target scattering given by

$$\sigma = \left|\sum_p \sqrt{\sigma_p e^{i\phi_p}}\right|^2 \quad (3)$$

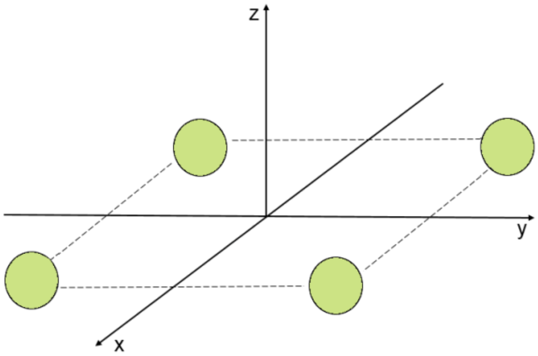
Where σ_p is the RCs of the p^{th} scatter and $\phi_p$is the relative phase of the p^{th} scatter.



(a) (b)



(c)



(d)

Fig. 3: Complex target modeling using four simple scatters of(a) complex sphere.(b) complex cylinder.(c) complex frustum. (d)complex circular disc.

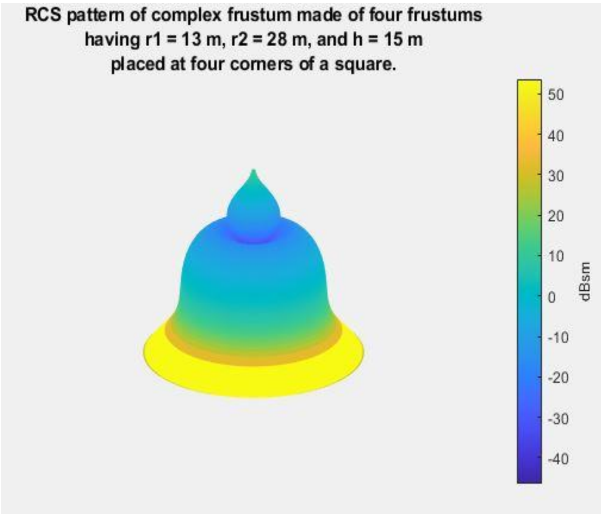


Fig. 4: RCS pattern for complex frustum.

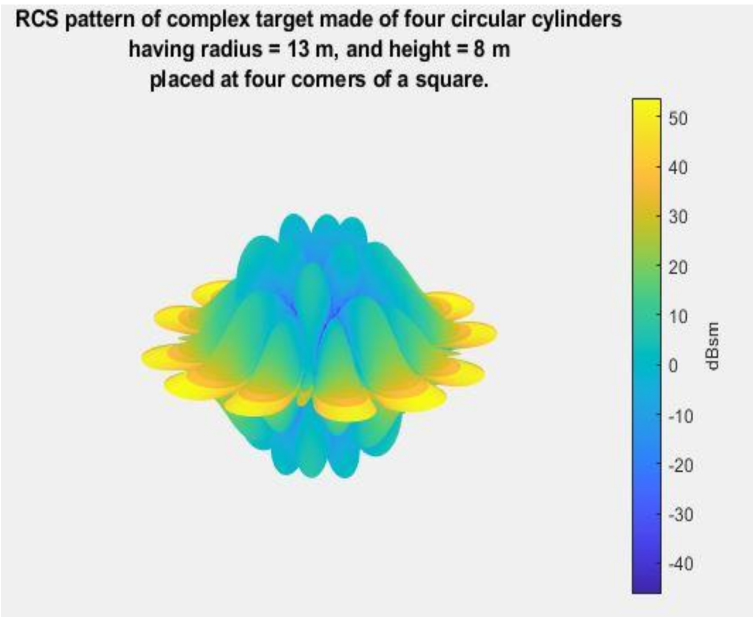


Fig. 5: RCS pattern for complex circular cylinder.

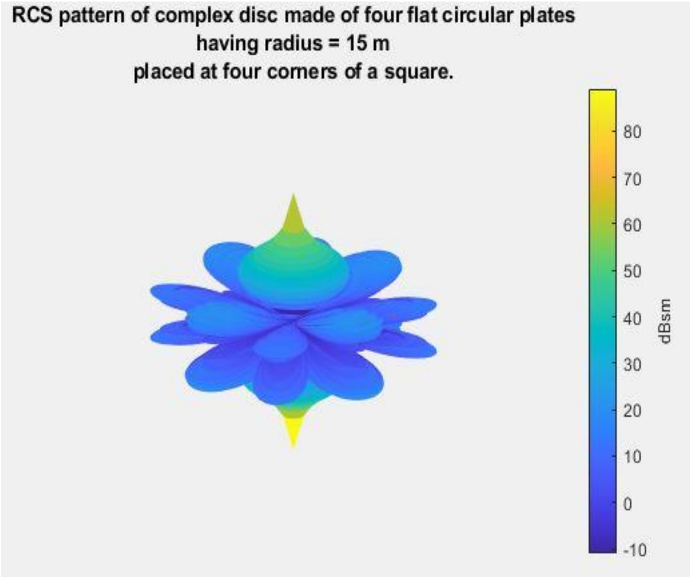


Fig. 6: RCS pattern for complex disc.

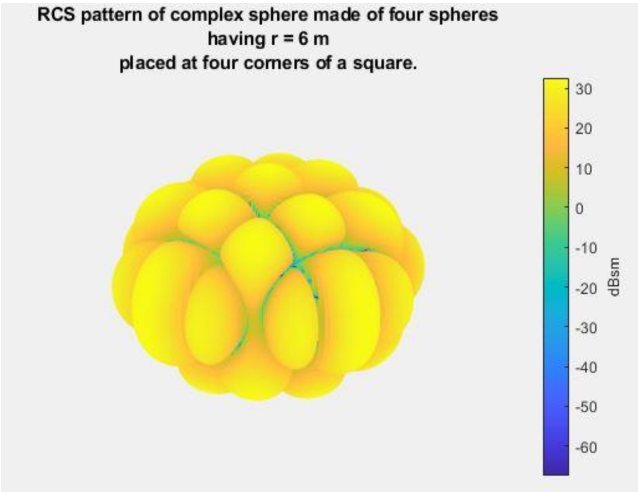


Fig. 7: RCS pattern for complex sphere.

III. FEATURE EXTRACTION

A. MODWPT

A finite frequency partition is used with the help of the Wavelet Packets. MODWPT is a non-decimated version of the Discrete Wavelet Transform (DWT) and it does not require any down-sampling like in DWT [5]. MODWPT is non-orthogonal and supports a signal of any sampling size. It produces a variance estimator that is more asymptotically efficient compared to DWT. The quadrature mirror filters are used to partition the sampling signal into sub-bands. The approximation or scaling coefficients are obtained by low pass filter and detailed/wavelet coefficients are obtained by the high pass filter. The obtained scaling and wavelet coefficients are equal in number and are equal to the number of the observation sets. If g(n), h(n) represents the mathematical form of low and high pass filters respectively, then they have the following properties:

$$\sum_{n=-\infty}^{\infty} g(n) = \sqrt{2}, \sum_{n=-\infty}^{\infty} g^2(n) = 1, \sum_{n=-\infty}^{\infty} g(n)h(n) = 0 \qquad (4)$$

$$\sum_{n=-\infty}^{\infty} h(n) = \sqrt{2}, \sum_{n=-\infty}^{\infty} h^2(n) = 1, \sum_{n=-\infty}^{\infty} h(n)g(n) = 0 \qquad (5)$$

MODWPT provides equal bands of frequency partition and it depends on the number of levels [6]. For jth level, it partitions the signal into 2^j sub-bands and the frequency of the nth node at the jth level will be in the range of $[\frac{f_s n}{2^{j+1}}, \frac{f_s(n+1)}{2^{j+1}}]$.

The decomposition of signal using MODWPT is given by

$$s_j^{2z}(k) = \frac{1}{\sqrt{2}} \sum_{n=-\infty}^{\infty} g(n)\, s_{j-1}^{z}(k-n) \qquad (6)$$

$$s_j^{2z+1}(k) = \frac{1}{\sqrt{2}} \sum_{n=-\infty}^{\infty} h(n)\, s_{j-1}^{z}(k-n) \qquad (7)$$

The reconstructed coefficients of MODWPT at any j^{th} level is given by

$$a_j^{2z}(k) = \frac{1}{\sqrt{2}} \sum_{n=-\infty}^{\infty} \tilde{g}(n)\, s_{j-1}^{2z}(k-n) \qquad (8)$$

$$a_j^{2z+1}(k) = \frac{1}{\sqrt{2}} \sum_{n=-\infty}^{\infty} \tilde{h}(n)\, s_{j-1}^{2z+1}(k-n) \qquad (9)$$

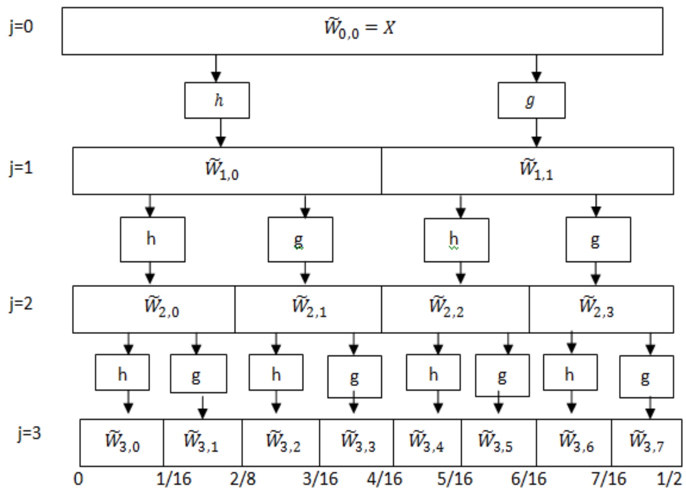


Fig. 8: Decomposition of signal into MODWPT coefficients $\widetilde{W}_{j,n}$ with levels j=1, 2, 3 and frequency index n ranging from 0 to $2^j - 1$.

IV. FEATURE SELECTION

Feature selection determines a minimal feature subset and improves the accuracy of the classifier while representing the original signal. Many feature extraction methods based on Shannon or

Information entropy are proposed and requires intensive computations. A heuristic approach namely, Relative Wavelet Energy Entropy is used for feature selection [7]. From each level, it extracts the features from the signal and detects the degree of similarity among them. For a jth level, energy associated at that level $\mathrm{E_j}$ is given by the sum of wavelet coefficients $\mathrm{C_j}$ at that sacle.

$$\mathrm{E_j} = \sum_{j} \left|\mathrm{C_j(k)}\right|^2 \tag{10}$$

Total energy of all the levels $\mathrm{E_{total}} = \sum_{j} \sum_{k} \left|\mathrm{C_j(k)}\right|^2 = \sum_{j} \mathrm{E_j}$

Now the Relative Wavelet energy is given by $\mathrm{RWE} = \frac{\mathrm{E_j}}{\mathrm{E_{total}}}$

If the degree of similarity is high between the extracted features of the signal, then they are considered or else ignored [8]. Thus, it can serve as heuristic information and increases the accuracy of the classifier performance.

V. CLASSIFIERS

The obtained reduced feature sets are given to different classifiers namely SVM, k-NN and ANN after portioning the feature data set into 70% as training dataset and rest of 30% as the testing dataset. This training data set is used to train the classifiers ahead. The classification of targets using SVM classifier is implemented by using Statistics and Machine Learning toolbox and for ANN classifier Neural network Toolbox is used.

A. Support Vector Machine

SVM classifier discriminates the targets by mapping the input vectors to higher dimensional space and a maximal hyper-plane is formed separating them. This hyper-plane can be viewed in two-dimension as a line separating the data on each side. The data is separated in such a way that it resembles two parallel hyper-planes separating them; the distance between them is called the margin. The greater the margin, the greater will be the separation of data or classes [9].

For a training set of (x_i, c_i), with x features, c class labels and i= 1,2 …K, SVMs is constructed from the following mathematical optimization procedure:

$$\text{minimize } [\tfrac{1}{2}\left(\mathrm{w^T w}\right) + \mathrm{C} \sum_{j=1}^{k} \epsilon_j] \quad \text{subject to } \mathrm{C_j}\left(\mathrm{w^T} \emptyset(\mathrm{x_i}) + \mathrm{b}\right) \geq 1 - \epsilon_j, \quad \epsilon_j \geq 0 \tag{11}$$

where, ω is the decision plane orientation vector

b is bias

ε_i is marginal slack variable

∅ is mapping function

C is penalty parameter of error term

The expected classification error for unseen test samples is minimized by finding a optimum linear hyper plane by SVM.

B. K-Nearest neighbour

k-NN is a supervised machined learning algorithm based classifier which is simple and easy to implement [10]. It compares the available training data with the given test data. It considers k nearest data points from the training samples that are close to the target/testing data sample and assigns the most occurring class among the training samples to that target [11]. By tuning the value of k for 3, 5,and 7 integers the performance of classifier is observed. The nearest neighbours are calculated by using the Euclidian distance criterion.

If $x_1 = \left(x_{1,1}, \ldots\ldots x_{1,k}\right)$ is training data set and test data is $x_2 = \left(x_{2,1}, \ldots\ldots x_{2,k}\right)$ then at any instant the Euclidian distance is given by

$$d(x_1, x_2) = \sqrt{\sum_{j=1}^{k}(x_{1,j} - x_{2,j})^2} \qquad (12)$$

C. Artificial Neural networks

ANN is a supervised learning approach and massively distributed parallel processors which use the multi perceptron to classify the classes of the targets [12]. It consists of one input layer, output layer and one or more hidden layers. The neural networks are composed of interconnected nodes. The weights associated with these nodes are optimized until a specified accuracy is achieved at the time of training. A feed forward network topology is used. The optimization depends on the accuracy and mean square error (MSE) during training and training [13]. It also consists of bias which improves the neural network performance and also an activation function to calculate the output response of the node. Once the final optimized design with minimum MSE is selected, the network is trained. The input to the neural network depends on number of feature vector instances while the output nodes depend on the number of classes [14]. The Trained network is tested and the validation of the trained network is observed along with the error prediction in the output. Here a single hidden layer is used.

VI. EXPERIMENTAL RESULTS

The results of this experimental study are organized into 2phases.

1. Data generation
2. Feature Extraction and Classifier models

A. Data generation

Data plays a prominent role in the field of machine learning and artificial intelligence. The machine learning models are realised by the tremendous sets of I/Q samples corresponding to the radar echoes obtained from the structures of the chosen targets shapes. Obtaining a real time data from radar targets is cumbersome and incurs a lot of expenditure. In order to overcome these limitations, a novel mechanism is developed where the desired target models are stimulated and are recognised with the help of the synthesized I/Q samples.Synthesised data is the data created from the various mathematical models replicating the real time scenarios using the software domain. To develop a target model, the operating parameters like frequency of operation (850MHz), set of elevation and azimuth scanning angles, velocity of signal propagation are chosen. Later, the desired geometrical shape is developed is considered and its parameters like height, radius are finalized. With the help of these parameters, the RCS patterns of the desired geometrical shapes by obtained with the help of the RCS mathematical equations of the corresponding shape. By applying the obtained RCS pattern to the backscattered RADAR target model, the returns from different aspect angles which changes from sample to sample are stimulated.For complex shaped targets, reflections can no longer be considered the same across all directions. The RCS changes with the aspect angles. Aspect dependent RCS patterns can be measured similar to antenna radiation patterns. The result of such measurements or models is a table of RCS values as a function of azimuth and elevation angles in the targets local coordinate system. The number of target shapes for which analytically derived RCS patterns exist are few. An alternative approach to model the complex targets is representing them as a collection of simple scatters. These scatters are of simple geometrical shapes. In our experimental study, we model complex targets using four scatters. The scatters are located at the four vertices of a square in the xy plane. We considered the four scatters to be identical in each complex structure and side length of the square is proportionately set with respect to the dimensions of the simple targets.By varying the dimensions, 10 different structures are considered for each geometric shape. A total of 40 RCS patterns are synthesized for 4 geometric shapes. For each structure, 250 motion profiles are simulated which accounts to 2500 (250x10) for each shape. 20 scans are performed in which 50 different aspect are considered for every scan resulting in 50 echoes per scan and 1000 (50x20) per target. A total of 10000 (2500*4) motion profiles are obtained for 4 geometric shapes.The motion profiles obtained from these non-fluctuating complex targets are considered to be raw features. This cannot help in discriminating the crucial information. By performing frequency domain analysis on this data, the significant information can be extracted to enhance the classification accuracy. The frequency extraction technique namely MODWPT is described in the subsequent section.

B. Feature extractionand Classifier models

The features are smaller in size compared to the original signal, making it easy to learn the recognition models. The frequency changes according to the motion of the target. With the help of Wavelet Transforms, focusing on the time-frequency characteristics of the signal gives efficient information. The time-frequency signatures derived by applying the wavelet transform will provide insights that train the learning models for target recognition. The frequency separation between four geometrical shaped targets exists and suggests a frequency domain measure to classify the signals. The MODWPT partitions the signal energy at the j^{th} level into 2^j sub-bands of equal energy. Thereby, the signal energy is also preserved. The relative sub-band energies are compared using the relative wavelet energy feature selection. By tuning the number of levels in MODWPT feature extraction, the feature set consists of 8, 16, or 32 predictions per target return. This reduces the feature set while preserving the information of the target in the original signal. This property will further improve the ability of the classifier to classify the targets.The extracted features are classified by partitioning them into 70% as training data and 30% as the testing data resulting in 7000 and 3000 feature set instances for the training and testing data respectively. From the 2500 feature vector instances per geometric shape, 1750 are assigned randomly for training the classifier, and the rest of 750 as testing data to assess the performance of the classifiers trained models. The classification models like SVM, kNN, and ANN are used. The output of the classifier's performance is obtained in the form of a confusion matrix and the results are observed.The performance metrics used for the classifier performance are:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{(TP+FN)+(TN+FP)}} \quad (13)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \quad (14)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (15)$$

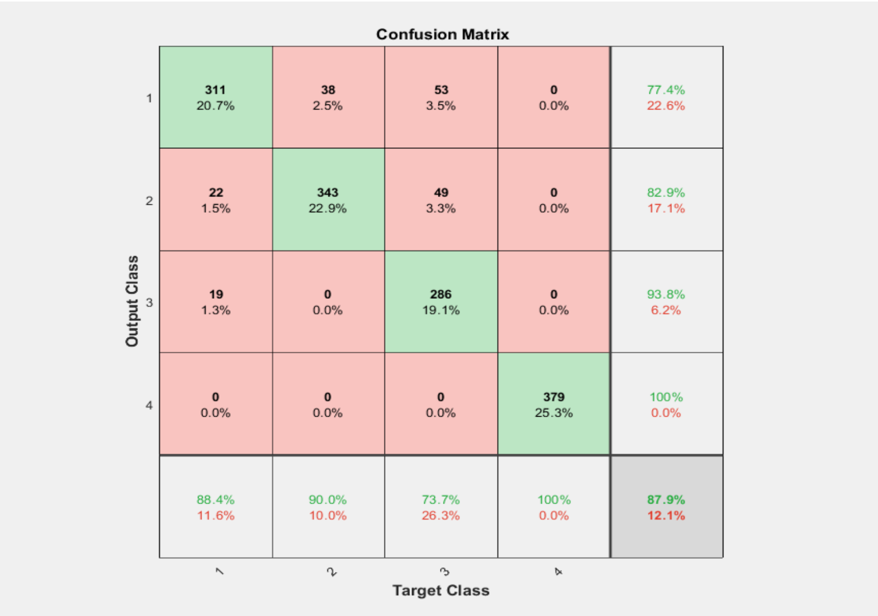
$$\text{Precesion} = \frac{\text{TP}}{\text{TP+FP}} \quad (16)$$

$$\text{F\_measure} = \frac{2(\text{Precision} \times \text{Sensitivity})}{(\text{Precision+Sensitivity})} \quad (17)$$

$$\text{G\_mean} = \sqrt{(\text{Specificity} \times \text{Sensitivity})} \quad (18)$$

From the obtained confusion matrix during analysis, it is observed that SVM gives an accuracy of 68.9%.

Similarly, the confusion matrix of ANN classifier model is given below which shows an accuracy of 87.9%.



The confusion matrix of k-NN classifier model is given below which shows an accuracy of 91.8%.

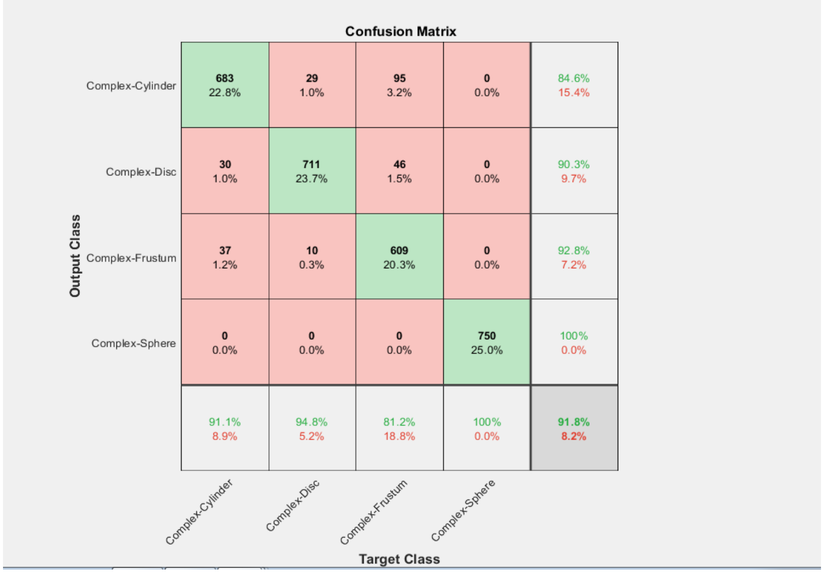


Table 1: Overall performance of the classifiers k-NN.

Metrics	complex cylinder	complex disc	complex frustum	complex sphere
Sensitivity	0.8463	0.9034	0.9284	1
Specificity	0.9694	0.9824	0.9398	1
Precision	0.9107	0.9280	0.8120	1
F1 Score	0.8773	0.9252	0.8663	1

Table2: Overall performance of the classifiers SVM.

Metrics	complex cylinder	complex disc	complex frustum	complex sphere
Sensitivity	0.6089	0.4749	0.9336	1
Specificity	0.7986	0.9618	0.8666	1
Precision	0.2907	0.9213	0.5440	1
F1 Score	0.3935	0.6268	0.6874	1

Table3: Overall performance of the classifiers ANN.

Metrics	complex cylinder	complex disc	complex frustum	complex sphere
Sensitivity	0.7736	0.8285	0.9377	1

Specificity	0.9627	0.9650	0.9146	1
Precision	0.8885	0.9003	0.7871	1
F1 Score	0.8249	0.8629	0.8254	1

VII. CONCLUSION

Dedicated machine learning models are developed for the complex targets as a combination of simple geometrical shapes and their RCS patterns are observed. The features are extracted from the raw data obtained from the radar returns using the MODWPT technique. Relative wavelet energy entropy feature selection proved to be a heuristic approach in reducing the features while retaining the original signal information. For different levels in MODWPT feature extraction, the classification models are trained and tested to distinguish the targets. By tuning various parameters in the respective classifier models, the performance metrics are calculated and are compared. It is observed that the k-NN classifier with k=5 has shown better results for the classification of the complex target with 91.8% accuracy with a 5 level MODWPT feature extraction.

References

[1] “Introduction to Radar Systems”, Merrill.I.Skolnik, Third Edition, McGraw-Hill, 2001

[2] Mahmoud Khodjet-Kesba, “Automatic target classification based on radar backscattered ultra wide-band signals”, Université Blaise Pascal - Clermont-Ferrand II, 2014.

[3] E. F. Knott, “Radar Cross Section”, in aspects of Modern Radar, E. Brooker (ed.), Norwood. MA: Artech House, 1988.

[4] Bassem R. Mahafza, “Radar systems analysis and design using Matlab”, second edition

[5] “ Comparison between Discrete Wavelet Transform and Maximal Overlap Discrete Wavelet Transform as an Analysis tool for H.264/AVC Video”, by Hiba H. S. M. Ali;Sami M. Sharif, ICCCEEE,2018..

[6] “Rolling Bearing Fault Feature Extraction and Diagnosis Method Based on MODWPT and DBN”,by Xiao Yu; Xiaohong Ren11th International Conference on WCSP, IEEE 2019.

[7] “A relative decision entropy-based feature selection approach”, by Jiang, Feng; Sui, Yuefei; Zhou, Lin (2015).

[8] “Relative wavelet energy as a tool to select suitable wavelet for artifact removal in EEG”, by M.D. Salwani; Y. Jasmy, 1st International Conference on Computers, Communications, & Signal Processing with Special Track on Biomedical Engineering,IEEE, 2005.

[9] Christianini, N., and J. Shawe-Taylor,“ An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods”, Cambridge, UK: Cambridge University Press, 2000.

[10]“Insider Threat Detection with Face Recognition and KNN User Classification”, by Sarma, M. S., Srinivas, Y., Abhiram, M., Ullala, L., Prasanthi, M. S., & Rao, J. R. , International Conference on Cloud Computing in Emerging Markets, IEEE, 2017.

[11]“Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine Classifiers for Land Cover Classification Using Sentinel-2 Imagery” by Phan Thanh Noi, and Martin Kappas, MDPI,2018.

[12] “Classification Using ANN: A Review”, by Rajni Bala , Dr. Dharmender Kumar, International Journal of Computational Intelligence Research, 2017.

[13]“ANN classification of ischemic stroke severity using EEG sub band relative power ration” W.R.W Omar, R. Jailani, ICSPC, 2014.

[14]“Classification of hardwood species using ANN classifier” by Yadav, A. R., Dewal, M. L., Anand, R. S., & Gupta S., Fourth National Conference on Computer Vision, Pattern Recognition, Image Processing and Graphics, IEEE. 2013.