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Jamming Efficacy Analysis of Chaff using AI/ML

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ABSTRACT

Chaff is a Passive Electronic Countermeasure technology that plays a pivotal role in war scenarios. It can be used as a passive jammer to shield a war platform effectively. It can mimic the platform's radar cross section (RCS) signature and act as a deceptive pseudo target. This manuscript presents an analysis of the jamming efficacy of chaff cloud. For this, three feature extraction and four AI/ML classification methods were employed, assuming that the Moving Target Indicator (MTI) and Doppler capabilities of the tracking radar are off. The effect of three different chaff deployment locations on its jamming performance has been analysed to determine the best possible deployment location. In the measurement setup, the range profile of the cloud is measured in the presence of a target. The classification performances of the extracted feature vectors are evaluated using the Support Vector Machine (SVM), Unsupervised Distance Classification (UDC), Naïve Bayes (NB) and Decision Tree (DT). A maximum 58.33 % decrease in recognition rate was observed with the introduction of chaff cloud when UDC and SVM approaches are employed and chaff is deployed from 90°. Noise has been introduced to closely predict the actual, practical performance of chaff in an actual deployment environment. The recognition rates fall less than 8.33 % for SVM and NB when AWGN (Artificial White Gaussian Noise) is 1.2 times. Based on these results, the jamming efficacy and the optimized tactical strategy of the chaff cloud are proposed. Better Out of the four AI/ML approaches, UDC and DT exhibit the best jamming performance and SVM exhibits the best anti-jamming performance. Any discrepancy and chances of overfitting can be avoided using a larger dataset with more features.

Keywords: Artificial intelligence; Chaff; Radar cross-section; Jamming efficacy; Machine learning; Range profile

NOMENCLATURE

SVM	: Support vector machine
UDC	: Unsupervised decision classification
NB	: Naïve bayes,
DT	: Decision tree
SCP	: Scattering center peaks
FL	: Feature length
DE	: Distribution entropy

1. INTRODUCTION

Radar jamming is a key component of electronic combat and electronic warfare. This includes creatieng false targets or altering the Radar Cross Section (RCS) signature of the true target to increase the survivability of radar which either deceptively mimics the true target or causes multiple reflections that disrupt the radar screen. The target platform dispenses chaff cloud to confuse the radar. RCS estimation is crucial in modern warfare as most radars use this to track targets. In general, the RCS of any object can be defined by Eqn. (1)[1].

$$\sigma = 4\pi R^2 \frac{|E_{scat}|^2}{|E_{inc}|^2} \tag{1}$$

where, 'E_{inc}' and 'E_{scat}' are the electric field strengths of incident and scattered wave, respectively and 'R' is the range from radar to the target.

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Till now, research on chaff primarily focuses solely on its scattering characteristics. To evaluate the jamming efficacy of the chaff cloud, the deployment platform should be taken into account and must not be overlooked. The jamming performance of the chaff cloud can be analyzed for various applications based on its electromagnetic scattering characteristics [2-5]. A high-speed moving target can be differentiated from a slow-settling chaff cloud by analyzing the Doppler effect. Similarly, the geometric characteristics of the target can be identified using Range profile data. Other features can further be derived from the range profile data for better recognition. The features can be compared with the features of a labelled target in the database using an AI approach[6-11]. AI can perform human intelligence-based complex tasks such as pattern recognition and classification with ease. A subset of AI is ML. Using ML algorithms, input data features are analysed and a classification model is created. The model is trained using 80 % data and the remaining 20 % is used to test the accuracy of the classifications.

In this manuscript (a) a novel experimental setup for measuring the performance of chaff cloud in the presence of a target is introduced (b) features are extracted based on geometrical attributes and further classified into chaff and target based on AI/ML algorithms, (c) best chaff dispensation location is identified (d) effect of environmental noise on jamming efficacy is analysed.

2. METHODOLOGY

A testing window is created using range profile data based on range and max amplitude of signal, max amplitude of background noise. Three features are chosen such that they are indicative of geometrical differences of the target with the chaff. The Scattering Centre Peaks (SCP) are one feature that is closely related to the geometrical configurations of chaff and target. It can be obtained from the number of peaks observed in range profile data. The feature-length (FL) is the second feature that estimates the propagation width of the object in the radial direction. This length is calculated by estimating the region in the range profile where maximum SCPs are found continuously. The FL expands when the chaff is used. The third feature is Distribution Entropy (DE) which indicates the concentration of scattering centres. This feature assesses the system's randomness or disorder. Entropy is introduced to depict the concentration of scattering centres within the target and the jammer. Additionally, the chaff cloud notably alters the scattering centres' entropy, consequently impacting target recognition. To compute entropy, normalization of the range profile (R) is initially conducted as follows:

$$\bar{R}(m) = \frac{R(m)}{\sum_{m=1}^{M} R(m)} \tag{2}$$

The entropy of the range profile is expressed as:

$$DE = -\sum_{m=1}^{M} \overline{RP}(m) \log_{10} \overline{RP}(m) \tag{3}$$

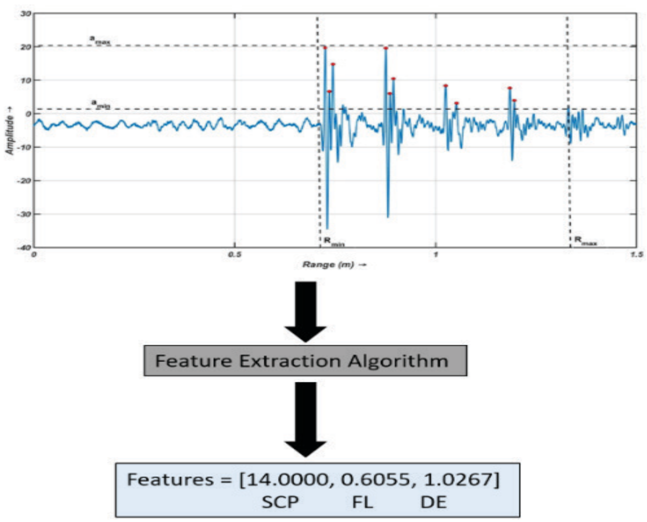

Figure 1. Research methodology for feature extraction and classification.

The research flow and methodology are well illustrated in Fig. 1. The classification performances of the extracted feature vectors are evaluated using the Support Vector Machine classification (SVM), Unsupervised Distance Classification (UDC), Naïve Bayes (NB) and Decision Tree (DT).

2.1 Unsupervised Distance Classification

The separation between two specified points in Euclidean space is given by UD. Each profile characteristic obtained correlates to a 3D point or spot in the space. All the three values i.e., SCP, FL and DE define the location of that point. Greater the similarities in profile characteristics, smaller will be the distance between the points irrespective of jamming, and hence making recognition of target difficult. Alternatively, reduced jamming efficiency is observed when UD is increased, therefore increasing the probability of detection.

$$d_1^i = \sqrt{(p_1^{tc}(i) - C_1^{plane})^2 + (p_2^{tc}(i) - C_2^{plane})^2 + (p_3^{tc}(i) - C_3^{plane})^2} \tag{4}$$

$$d_2^i = \sqrt{(p_1^{tc}(i) - C_1^{chaff})^2 + (p_2^{tc}(i) - C_2^{chaff})^2 + (p_3^{tc}(i) - C_3^{chaff})^2} \tag{5}$$

Increment the value of N_{suc} by one if $d_1^i > d_2^i$ otherwise, nothing is to be done. The recognition rate, and hence the jamming efficiency of the chaff cloud is estimated using (6) once the traversing of the chaff cloud is done over the entire target's range profile.

$$R_{rec} = \frac{N_{suc}}{M} \times 100\% \tag{6}$$

2.2 Support Vector Machine classification

For tasks involving classification, a powerful machine learning algorithm, SVM, is commonly used. Range Profile characteristics including that of chaff cloud, target and chaff cloud along with the target are estimated at different positions. A data set can be obtained by retrieving the attributes from all the range profile characteristics. In addition, the range profile coordinates of the target with chaff cloud are included. Class labels of Target and chaff cloud are designated by 1 and 0 respectively. Further, their corresponding feature sets are designated as D1 and D2. Points obtained from both sets are labelled as ($t_1^t(i)$, $t_2^t(i)$, $t_3^t(i)$). Data space is divided into two sub-spaces by the parameterized plane wt′ + = 0 resulting in the least amount of classification inaccuracies, such that –

$$D1 = \{t: wt' + \alpha \leq 0\}$$

$$D2 = \{t: wt' + \alpha > 0\} \tag{7}$$

Transpose of the vector t is denoted by t′. Depending on the majority rule, label sets D1 (Target) and D2 (Chaff Cloud) correspond to 1 and 0 and are represented by D1 and D2 respectively. The procedure of parameter selection, the process of w and α is accomplished once the following conditions are satisfied -

$$\min_{w,\alpha}(err_{d1} + err_{d2}) \tag{8}$$

where,

$$err_{d1} = \frac{card(\{t \mid t \in d_1,\ t \in D_2\})}{card(d_1)} \tag{9}$$

$$err_{d2} = \frac{card(\{t \mid t \in d_1,\ t \in D_2\})}{card(d_1)} \tag{10}$$

The overall elements in the data set are provided by the card() function and the best optimal values i.e., w_{best} and α_{best} are found post-optimization.

2.3 Naive Bayesian Classification

The statistical classifier method called Bayesian classifiers is used to determine the particular class of the tuple to infer its class membership. Bayesian classifiers are formed by computing them along with their frequency occurrence in the training stage. In accordance to this theorem:

$$P(y_i \mid \mathbf{p}) = \frac{P(p \mid y_i) \cdot P(y_1)}{P(p)} \tag{11}$$

where, dependent vector p denotes the feature acquired from the chaff cloud and target range profiles and y_i gives the expected class of test range profile.

2.4 Decision Tree Classification

The decision tree is constructed using a standard algorithm that partitions the feature space based on thresholds for SCP, FL, and DE. The process involves calculating entropy for node splitting and maximizing information gain. Entropy is a measure of the impurity or randomness in the data. For a binary classification problem, the entropy H for a node can be calculated as:

$$H = -p_0 \log_2 p_0 - p_1 \log_2 p_1 \tag{12}$$

where, p_0 is the proportion of target (label 0) and p_1 is the proportion of chaff (label 1) in the node. Information gain measures the reduction in entropy after a dataset is split on an attribute. For an attribute A, the information gain IG can be calculated as:

$$IG(A) = H(\text{parent}) - \sum(v \in \text{values}(A)) \left(\frac{|Sv|}{|S|}\right) H(S_v) \tag{13}$$

where, H (parent) is the entropy of the parent node, Sv is the subset of the data where attribute A has value v, and $H(S_v)$ is the entropy of subset S_v. The decision tree consists of a series of decision nodes that split the feature space based on thresholds for SCP, FL, and DE to classify each measurement as either target or chaff. The attribute that maximizes the information gain is chosen for splitting the node. After calculating the entropy for the parent node using (12), for each possible split on a feature, the entropy of the subsets created by the split is calculated. Upon calculating the IG for each split, the attribute and the threshold that result in the maximum information gain are selected.

3. MEASUREMENT SETUP

A scaled-down model of the chaff cloud was made with the help of a non-conducting cubical frame (30 cm × 30 cm × 30 cm) in which the cloud was distributed to be spatially random. Similarly, five circular discs of diameter 6 cm each were attached to an aluminium sheet of size 2 feet × 1 feet to mimic target RCS for various range profile measurements as shown in Fig. 2.

Figure 2. Scaled-down model of the chaff cloud (30 cm x 30 cm x 30 cm) and target.

The indoor measurements were performed in an anechoic chamber to investigate the jamming performance of the chaff cloud according to the methods mentioned above.

The RCS measurements of the samples were carried out using an in-house anechoic chamber measurement facility at the Defence Laboratory, Jodhpur (DLJ). The chamber, as shown in Fig. 3, is of size 14 m (L) x 8 m (W) x 8 m (H) and operates in the frequency range of 2 GHz to 18 GHz. The facility is capable of doing mono-static RCS measurement from 2 GHz to 18 GHz using time domain instrumentation which enables RCS measurement & ISAR imaging. It has automatic calibration with a standard reference target and filters to eliminate GSM frequencies to reduce errors.

To estimate the jamming efficacy, the chaff is placed along with the target on a turntable as shown in Fig. 4. The target is kept on the turntable and is rotated by angle θ_S. This angle is varied uniformly to cover the entire 360° view. These test positions (P_1, P_2, P_3,…, P_{12}) are shown in Fig. 5. The range profile of this composite model is measured along these directions. The chaff cloud is kept relatively fixed to the target at angle θc. This indicates the dispensation location of the chaff. Three configurations (C_1, C_2, C_3) have been considered where the chaff clouds are placed at 0º, 90º and 180º respectively.

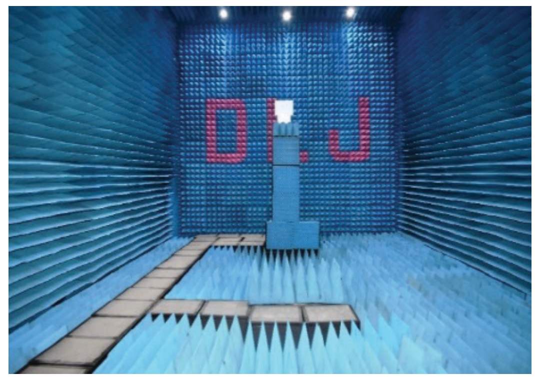

Figure 3. Indoor dynamic RCS measurement facility at Defence Laboratory, Jodhpur.

Figure 4. Target with a chaff cloud is placed on the upper surface of a turntable.

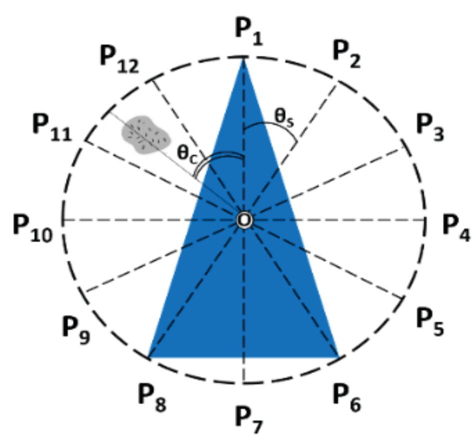

Figure 5. Directions for obtaining the range profile of the target along with chaff.

Table 1. UDC without noise

Index	Recognition rate (%)		
	Without chaff	With chaff	Decrease
C_1	91.67	66.67	24.99
C_2	91.67	33.33	58.33
C_3	91.67	75	16.67

Table 2. SVM without noise

Index	Recognition rate (%)		
	Without chaff	With chaff	Decrease
C_1	91.67	58.33	33.33
C_2	91.67	33.33	58.33
C_3	91.67	50	41.66

Table 3. NB without noise

Index	Recognition rate (%)		
	Without chaff	With chaff	Decrease
C_1	75	66.67	8.33
C_2	66.67	33.33	33.34
C_3	75	75	0

Table 4. DT without noise

Index	Recognition rate (%)		
	Without chaff	With chaff	Decrease
C_1	83.33	41.67	41.66
C_2	91.67	25	66.67
C_3	50	41.67	8.33

Subsequently, the effect of noise is introduced to get a closer estimate of real-world jamming performance. For this, additive white Gaussian noise (AWGN) is introduced into the measured data. Different levels of noise were taken at 0.1, 0.4 and 1.2 times the input.

4. RESULTS AND DISCUSSION

The recognition rates for different classification algorithms are tabulated in Tables I, II, III and IV. It can be observed that the recognition rate without noise decreases with the involvement of chaff, making it difficult for the enemy to identify the actual target.

The influence of noise on the recognition rate of the target is shown in Tables V, VI, VII and VIII. It can be found that the recognition rates of the target decrease when the Gaussian noise is introduced. This indicates that the noise of the environment significantly influences the target recognition.

The echo of the target in the presence of environmental noise confuses the recognition algorithms making it difficult to extract the geometric attributes of the target. It is also evident that an increase in noise levels completely distorts the target information and thus, the recognition rates of the target decrease sharply. The recognition rates fall less than 10 % when AWGN is 1.2 times. It can also be observed that the recognition rate in all scenarios is the lowest for C_2. Thus, chaff dispensation at $\theta_C = 90°$ offers better jamming efficacy than the other two configurations.

Table 5. UDC with noise

Index	Recognition rate (%)							
	Without chaff	With noise			With chaff	With noise		
		0.1×	0.4×	1.2×		0.1×	0.4×	1.2×
C_1	91.67	83.33	41.67	0	66.67	66.67	41.67	16.67
C_2	91.67	91.67	41.67	0	33.33	41.67	16.67	0
C_3	91.67	91.67	16.67	8.33	75	58.33	16.67	0

Table 6. SVM with noise

Index	Recognition rate %							
	Without Chaff	With Noise			With Chaff	With Noise		
		0.1×	0.4×	1.2×		0.1×	0.4×	1.2×
C_1	91.67	91.67	50	0	58.33	41.67	33.33	8.33
C_2	91.67	91.67	50	0	33.33	33.33	16.67	0
C_3	91.67	91.67	50	0	50	33.33	25	0

Table 7. NB with noise

Index	Recognition rate (%)							
	Without chaff	With noise			With chaff	With noise		
		0.1×	0.4×	1.2×		0.1×	0.4×	1.2×
C_1	75	75	66.67	0	66.67	41.67	33.33	8.33
C_2	66.67	66.67	66.67	8.33	33.33	8.33	0	0
C_3	75	66.67	66.67	16.67	75	16.67	8.33	0

Table 8. DT with noise

Index	Recognition rate %							
	Without chaff	With noise			With chaff	With noise		
		0.1×	0.4×	1.2×		0.1×	0.4×	1.2×
C_1	83.33	75	33.33	8.33	41.67	33.33	16.67	0
C_2	91.67	75	58.33	8.33	25	16.67	8.33	0
C_3	50	75	50	8.33	41.67	33.33	0	0

5. CONCLUSION

This manuscript estimates the jamming efficacy of chaff clouds in the presence of a target platform. Initially, a scaled-down cubical model of the cloud is developed. Indoor measurements are conducted to obtain the RCS and range profile information of the chaff cloud along with the target. The position of the cloud is kept fixed with respect to the target at different angles for various chaff dispensation locations. The features extracted from the measured data are then subjected to four AI/ML classification methods to evaluate the jamming performance.

It can be observed that the target recognition rate decreases in the presence of a chaff cloud. This enhances the survivability of the platform. As evident from the results, better jamming performance can be achieved when UDC and DT methods are used. Since the dataset is small and low dimensional, DT might overfit due to its tendency to create complex models. Hence, the target recognition capability is the least for DT.

The best anti-jamming performance can be achieved by using the SVM method. The impact of environmental noise is also evaluated for noise levels that are 0.1, 0.4 and 1.2 times the signal level. With the increase in noise level, recognition of the target becomes increasingly difficult. It is also found that releasing the chaff at 90^o gives the best jamming performance as compared to other locations. In the future more features, classification algorithms and a larger dataset can be used for more accurate predictions.

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Mr Anshul Mathur obtained BTech in Electronics and Communication Engineering from JIET, Jodhpur.
Her contribution to the presented work includes preparation of scaled down samples of chaff and performing their RCS measurements in anechoic chamber.

Mr Umesh Kumar has contributed to the present work by drafting the manuscript and performing range profile analysis using RCS measurements.

Mr Verandra Kumar obtained BTech from MNIT, Jaipur in ECE.
He has drafted the measurement and modelling procedures and carried out RCS measurements of various samples in the anechoic chamber.

Mr Alok Basita obtained BTech from MNIT. In the current work, he has contributed by providing insights and reviewing the methodology of RCS measurement.

Dr Prashant Vasistha obtained PhD from Department of Electronics engineering, IIT-BHU.
In the current work, he has played a crucial role in developing the methodology by providing overall guidance and reviewing the simulation as well as experimental results.