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Augmented Doppler Filter Bank for Enhancing Targets Detection Based on Machine Learning

***Abstract**. Radar Target Detection (RTD) is a critical aspect of modern radar systems that have widespread use in both civil and military fields. However, detecting targets in clutter and unfavorable conditions is challenging with conventional signal processing approaches such as Constant False Alarm Rate (CFAR). The harsh and complex environments in radar measurements make the target detection problem even more challenging when using traditional methods. Therefore, developing a reliable and robust RTD technique is crucial. This paper proposes an approach that incorporates Machine Learning (ML) with conventional methods to detect, separate, and classify real targets from noisy backgrounds in a real radar dataset by employing Fuzzy C-means (FCM) clustering to segment the Range Doppler Map (RDM) image into targets and background, then a feature extraction technique based on gray-level co-occurrence matrix (GLCM) and classify the targets using a support vector machine (SVM). The approach is based on an augmented Doppler Filter Bank (DFB) with RDM images and has been tested on a Frequency Modulated Continuous Wave (FMCW) radar mounted on an Unmanned Aerial Vehicle (UAV) for detecting ground targets. A flight was conducted in a challenging environment to evaluate the proposed system's performance. The experimental results demonstrate that the proposed approach outperforms existing methods in terms of classification accuracy. The proposed approach is also computationally efficient and can be easily implemented in real-time systems and has great potential in improving RTD performance in various applications.*

***Streszczenie.** Radarowe wykrywanie celów (RTD) to krytyczny aspekt nowoczesnych systemów radarowych, które są szeroko stosowane zarówno w zastosowaniach cywilnych, jak i wojskowych. Jednak wykrywanie celów w bałaganie i niesprzyjających warunkach jest trudne przy konwencjonalnych metodach przetwarzania sygnału, takich jak stała częstość fałszywych alarmów (CFAR). Trudne i złożone środowiska w pomiarach radarowych sprawiają, że problem wykrywania celu staje się jeszcze większym wyzwaniem przy użyciu tradycyjnych metod. Dlatego kluczowe znaczenie ma opracowanie niezawodnej i solidnej techniki BRT. W tym artykule zaproponowano podejście, które łączy uczenie maszynowe (ML) z konwencjonalnymi metodami wykrywania, oddzielania i klasyfikowania rzeczywistych celów z hałaśliwego tła w prawdziwym zbiorze danych radarowych poprzez zastosowanie klastrowania rozmytych średnich C (FCM) w celu segmentacji mapy Range Doppler (RDM)) na cele i tło, a następnie technikę ekstrakcji cech opartą na macierzy współwystępowania na poziomie szarości (GLCM) i klasyfikować cele za pomocą maszyny wektorów nośnych (SVM). Podejście to opiera się na rozszerzonym banku filtrów dopplerowskich (DFB) z obrazami RDM i zostało przetestowane na radarze fali ciągłej z modulacją częstotliwości (FMCW) zamontowanym na bezzałogowym statku powietrznym (UAV) w celu wykrywania celów naziemnych. Przeprowadzono lot w trudnym środowisku, aby ocenić wydajność proponowanego systemu. Wyniki eksperymentów pokazują, że proponowane podejście przewyższa istniejące metody pod względem dokładności klasyfikacji. Proponowane podejście jest również wydajne obliczeniowo i może być łatwo zaimplementowane w systemach czasu rzeczywistego oraz ma ogromny potencjał w zakresie poprawy wydajności RTD w różnych zastosowaniach. (**Bank rozszerzonych filtrów Dopplera umożliwiający lepsze wykrywanie celów w oparciu o uczenie maszynowe**)*

Keywords: doppler filter bank, moving target detector, radar signal processing, fuzzy c-means cluster, support vector machine.
Słowa kluczowe: bank filtrów dopplerowskich, detektor ruchomych celów, przetwarzanie sygnału radarowego, rozmyty klaster c-średnich, maszyna wektorów nośnych.

Introduction

In the past decade, radar technology has become increasingly important for detection and tracking purposes across a wide range of applications. Radars have the unique ability to operate with reasonable precision under diverse weather conditions and provide valuable information about the range, azimuth, height, and speed of targets. As a result, modern radar systems have been developed to meet the increasing demand for superior performance in various civil applications, including automotive radar, air traffic control, aircraft navigation, remote sensing, ship navigation and safety, law enforcement, and many other fields.

In addition to civil applications, radar technology has also found widespread use in agricultural, forestry, soil moisture monitoring, geology, geomorphology, and hydrology, as well as in oceanography, land use, and land cover mapping. However, radar systems have also been widely employed in military applications such as land-based air defense radar, missile control radar, airborne fire-control radar, airborne surveillance radar, coastal and naval surveillance, and navigation radar.

Overall, the development and advancement of radar technology has enabled its adoption in diverse applications, from civilian to military, making it a vital tool in various fields that rely on precise and accurate detection and tracking [1]. Despite the ability of radars to operate in severe and diverse environmental conditions, their measurement accuracy can still be affected by several factors. These include harsh environments, the maneuverability of moving targets under strong clutter and interference conditions, and targets with low signal-to-noise ratio. Thus, there is a considerable need to develop efficient and robust approaches for detecting and classifying moving targets. In response, various algorithms and approaches have been developed over the years to overcome the limitations associated with radar measurements and improve the probability of detecting moving targets.

The detection of radar targets and extraction of information from their echo signals is a commonly used technique to identify the desired target among the complex and noisy background. The reflected signals from the target are often buried within a mixture of noise, clutter, and jamming, making it necessary to employ techniques such as RTD to extract useful information. Digital signal processing is a crucial element of RTD, as it helps to distinguish between stationary and moving targets, utilizing tools such as Moving Target Detector (MTD) [2].

The MTD is a crucial aspect of RTD, which utilizes digital signal processing to differentiate between stationary and moving targets. The MTD relies heavily on the DFB, which comprises a collection of filters used for detecting targets. Incoming radar signals are received from various sources and sorted in the DFB based on their Doppler frequency. Typically, DFBs are constructed using the Fast Fourier Transform (FFT) algorithm, and their filters are designed to pass narrowband frequencies based on the number of samples in the received signal.

After the MTD, CFAR is applied to detect actual targets by comparing the sample value with a threshold at each Pulse Repetition Interval (PRI). The threshold is estimated based on some a priori knowledge about the clutter situations. The accuracy of CFAR is determined by the statistical properties of the signal and the probability of detection. The effectiveness of the radar is determined by its probability of detection and the probability of false alarms.

Many researchers have explored the use of ML techniques to develop intelligent signal processing methods for target detection. These algorithms aim to integrate radar measurements and parameters with various ML approaches, including Decision Tree (DT), Random Forest (RF), SVM, and empowerment techniques. Additionally, automatic feature learning methods such as Deep Learning (DL), Deep Belief Networks (DBN), Feed Forward Neural Networks (FNN), Deep Reinforcement Learning (DRL), Auto Encoder (AE), Long-Short Term Memory (LSTM), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Generative Adversarial Networks (GAN) are employed. The ultimate goal of these techniques is to improve the target detection process by using a variety of strategies [3,4].

While ML and DL techniques have shown great potential in improving the probability of detection and reducing false alarm rates in modern radar systems compared to traditional signal processing methods, the accuracy of these models is still dependent on the amount of training data. Additionally, the complexity of these models can increase the processing time required for target detection [5].

The objective of this study is to propose a robust and efficient system that can overcome the limitations of both conventional and combined RTD techniques with various ML algorithms. The proposed system offers several key contributions. Firstly, it enhances the probability of detecting the desired targets and decreases the false alarm rate when compared to the CFAR detector, through the use of ML algorithms.

In this paper, we propose an augmented DFB approach for RTD that utilizes image processing techniques for RDM segmentation and feature extraction, followed by target classification using SVMs. Specifically, the proposed approach uses FCM clustering to segment the RDM image into targets and background, and GLCM to extract texture features of the segmented targets. The SVM classifier is then trained on the extracted features to classify the targets accurately.

This paper is organized as follows: In Section 2, we review related works in the field of RTD. Section 3 presents the proposed augmented DFB approach for RTD. Section 4 describes the experimental setup and results. Finally, Section 5 concludes the paper and discusses future directions for research in this area.

Related Work on Radar Target Detection

Echo signals received by a radar system are often accompanied by noise, clutter, and jamming. During radar signal processing, various techniques such as matched filtering, DFB, zero velocity filter, and CFAR detection are employed to process the reflected signals. In order to achieve high-range resolution and a narrow pulse width, the radar signal is sampled at a specific rate and then compressed using a matched filter. Doppler processing is then applied to multiple pulses at each range unit to obtain the Range-Doppler spectrum maps. The CFAR detector is used to determine which Range-Doppler signal has higher energy than the detection threshold by analyzing the reflected signal amplitude stored in separate cells. Zero velocity filters are used to isolate low Doppler targets and clutter, and a clutter map and threshold detector are then applied to the output. Finally, the velocity and position of the target can be determined.

The conventional method uses statistical hypothesis testing to set an adaptive detection threshold that adjusts based on the levels of noise and clutter energy. Consequently, setting the threshold too low results in more targets being detected, but also increases false alarms. Conversely, if the threshold is set too high, the number of false alarms is expected to decrease, but fewer targets will be detected. Most CFAR schemes use statistical hypothesis testing to set the adaptive detection threshold based on the levels of noise and clutter energy. However, to estimate the level of background noise around the Cell Under Test (CUT), cells immediately adjacent to the CUT, known as guard cells, are excluded from the calculation. The local power level is estimated by slightly increasing the average power level, allowing for the limited sample size, and forming the threshold level. If the signal in the CUT exceeds the threshold and is greater than all of its adjacent cells, it is considered an object. This straightforward method is referred to as Cell-Averaging CFAR (CA-CFAR), while other approaches use the Greatest-Of (GO-CFAR) or Smallest-Of (SO-CFAR) to define the local threshold.

However, CFAR may not perform well in two scenarios. The first is when the clutter power suddenly changes within a signal, known as clutter edges, which can lead to performance decay and increased false alarms. The second scenario occurs when more than one object is present, causing the threshold level to rise and leading to the masking effect, where the weak echoes of distant targets are missed by the primary object [6].

Researchers have recently explored various ML-based approaches for target detection. For instance, Hu and Qi developed an adaptive detector that uses a neural network-based approach to determine the appropriate CFAR for the estimated environment [7]. Khalid et al. researched radar Range-Doppler for automatic target recognition using Convolutional Long Short-Term Memory (CLSTM) [8]. Akhtar and Olsen trained an Artificial Neural Network (ANN) using a Cell-Averaging CFAR (CA-CFAR) and fixed the errors of the CA-CFAR to achieve a lower false alarm rate [9]. Thornton used neural networks to solve the radar clutter classification problem [10]. Numerous research has been developed over time to exploit convolutional neural networks for the sake of radar target identification in complex, nonstationary, and cluttered scenes. A signal detector has been developed based on a joint time-frequency analysis of radar imagery for target detection [11,12].

Although these ML and DL methods have benefited over traditional radar signal processing techniques to improve the probability of detection and reduce the false alarm rate, their accuracies are affected by the amount of training data. Moreover, the complexity of such trained models increases the time required to detect targets [13,14]. A CNN detector for single targets in homogeneous interference was developed by Yavuz et al [15]. Akhtar et al. presented an ANN-CFAR detector that can detect fluctuating targets in noisy backgrounds. Clutter detection is more common but more challenging than detecting targets within noise backgrounds [16].

System Overview

This section presents the hardware setup for the proposed system, which aims to address the limitations of conventional signal processing techniques and improve RTD by separating noisy background from desired echo signals. Fig. 1 illustrates the block diagram of the proposed system.

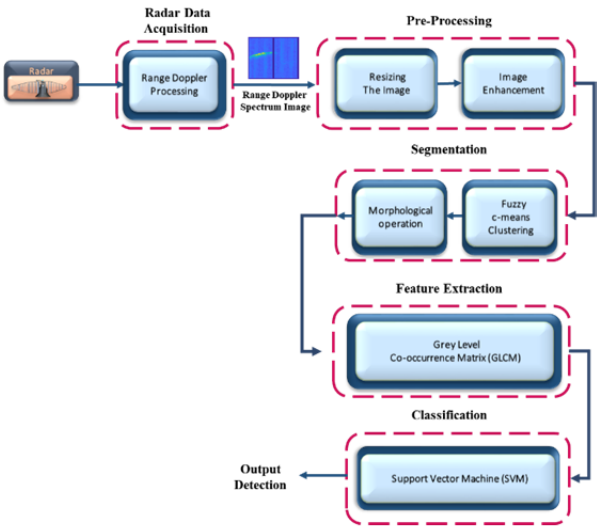

Fig.1. RTD system block diagram

Hardware Setup

The proposed augmented DFB system utilizes an FMCW radar with an operational frequency of 24 GHz. This radar has an accuracy of +/- 10 degrees in the elevation plane and +/- 15 degrees in the azimuth plane, with a resolution of 0.1 degrees. It consists of one transmitter and three receiver microstrip patch antennas and has a detection range of up to 100 meters for people and 300 meters for vehicles, with a resolution of 1 meter.

To control the quadcopter, a Pixhawk-2 autopilot is employed, which is equipped with several sensors, including an MS5611 barometer, a U-Blox GPS, and an InvenSense MPU-6000 MEMS IMU. The maximum useful payload of the quadcopter is 420g. During the experiments, the payload includes the radar system located at the belly of the UAV, which is connected to a BULLET-M, 2.4 GHz 28dBm transmitter with an Omni-directional antenna (BM2HP by Ubiquity) through ethernet. The transmitter and the radar are powered by a 3S Lipo battery, separate from the quadcopter battery. To receive the data from the radar, a Nano Station-M with a directive panel antenna and dual-polarity is connected to the ground station, as shown in Fig. 2. This setup aims to address the challenges associated with conventional signal processing techniques and improve the RTD by separating the noisy background from the desired echo signals.

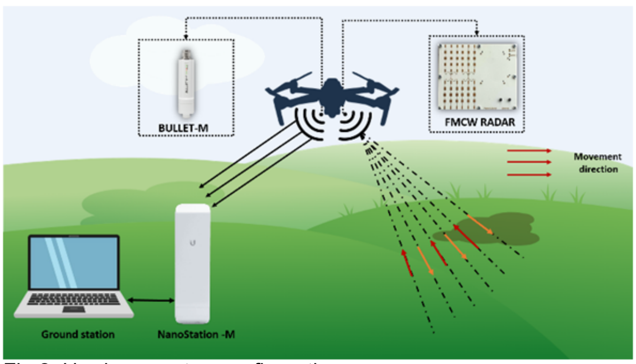

Fig.2. Hardware setup configuration

Radar Data Acquisition

During the flight, a micro-radar attached to a UAV emits a frequency-modulated sawtooth chirp to detect moving targets. The frequency at which the radar transmits ($f_{RF\,TX}$) can be expressed as a function of time as the chirp sweeps across ground objects:

(1) $$f_{RF\,TX} = f_c + \alpha\, t \qquad , 0 \le t < T$$

(2) $$\alpha = \frac{B}{T}$$

The carrier frequency of the radar is represented by f_c, α denotes the frequency sweep rate, B is the bandwidth of the transmitted chirp signal, and T is the duration of frequency sweep. The emitted signals are directed towards the target, and the reflected signals are received by the radar after a propagation time delay Δt, along with a small frequency shift Δf between the two transmitted frequencies. These time and frequency shifts occur due to the propagation effects over the range. The propagation delay time between the transmitted and received signals can be expressed as:

(3) $$\Delta t = 2\frac{\mathrm{R}}{c}$$

Where R is the range between the radar antenna and each scattered inside the beam width of the radar, and c is the speed of light. The frequency of the received signal is shifted by a time delay Δt, which can be expressed as:

(4) $$f_{RF\,RX} = f_c + \alpha * (t - \Delta t) \;, \Delta t \le t < T + \Delta t$$

Afterwards, the received signal is combined with the transmitted signal and then filtered through a low-pass filter to extract the video signal $x(t)$ which has a low beat frequency f_b, given by:

(5) $$f_b = \alpha * \Delta t$$

By substituting from Eqn. (2,3) in Eqn. (5), f_b can be rewritten as:

(6) $$f_b = \frac{B}{T} * 2\frac{R}{c}$$

The phase changes of the video signal x(t) are used to extract the Doppler frequency $f_{doppler}$, which provides information about the velocity of the target. The FMCW radar used in this study has a repetition rate of 12.150 kHz for the transmitted chirps and takes 256 sampling points per chirp at a sample rate of 264 ns.

The MTD signal processor uses a bank of Doppler filters as its core to reduce clutter and noise. This filter bank is implemented using the FFT algorithm.

After digitizing the received radar signal with an A/D converter, a baseband signal is generated. The proposed system's algorithms for target decision-making are based on FFT after Range-Doppler processing. The first step in processing the received signal is to perform an FFT to determine range information over the "fast time" for each sample. This process is repeated for each chirp that forms a frame. Once all chirps in a frame are processed, a Doppler-FFT is performed to determine the target's velocity, which is evaluated once per frame every N chirps in what is known as "slow time." The third dimension of the radar cube contains spatial information about the target's position, which is derived from the combined spatial information along all channels.

Once the received signals from the three antennas have been Fourier transformed, a mean Range-Doppler Map (RDM) is produced by averaging the RDM obtained from each antenna. The resulting map has 256x256 pixels, with each pixel assigned a 32-bit amplitude value. The horizontal axis of the RDM image represents the velocity measurements, while the vertical axis shows the range measurements. Each pixel of the RDM contains a 32-bit value that represents the intensity of the received signals from the different earth scatters. Figure 3 displays the RDM image.

The map is obtained by connecting to the radar through Ethernet, after the signal processing described above is performed inside the radar. This resulting image is then utilized for the purpose of target detection [17,18].

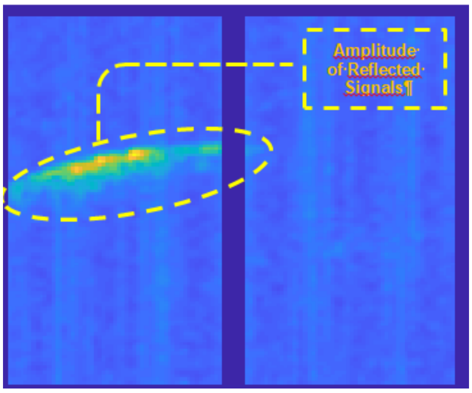

Fig.3. Reflected ground signals in the RDM image

Target Detection

The proposed methodology comprises several key stages, including enhancement, clustering, feature extraction, and the use of an SVM classifier with RDM images. The experiment was conducted on a dataset containing 510 RDM images using MATLAB (R2022a).

Pre-processing

Image enhancement preprocessing involves a set of techniques utilized to enhance the quality or clarity of an image before further analysis or processing. The main objective of image enhancement is to make the image easier to interpret or extract features from, while preserving its original content and structure. It is an essential step in improving the quality and usability of digital images, as illustrated in Figure 4.

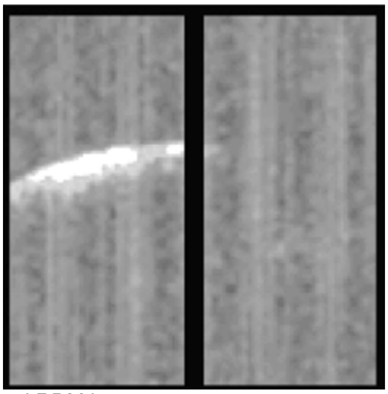

Fig.4. Enhanced RDM image

Some of the techniques used in image enhancement preprocessing include:

- Image resizing: This technique changes the size of an image, which can be useful for adjusting the resolution or aspect ratio to match specific requirements.
- Contrast enhancement: This technique adjusts the brightness and contrast of an image to improve the visibility of details that may be difficult to see in low contrast or dimly lit images.
- Sharpening: This technique enhances the edges of objects in an image to make them appear more distinct and clearer.
- Noise reduction: This technique removes unwanted noise or artifacts from an image, which can be caused by low light conditions or sensor limitations.

Segmentation

Bezdek proposed the FCM clustering algorithm, which is primarily used for pattern recognition. FCM allows a pixel to belong to more than one cluster, and its goal is to divide a given dataset into a positive number of clusters based on two parameters. In the context of RDM image segmentation, FCM was employed to identify the target region in RDM images. The FCM clustering method yielded satisfactory segmentation results [19].

The FCM clustering algorithm allows pixels to belong to multiple categories by utilizing fuzzy memberships. Let $Xz = (x1, x2, \dots, xN)$ denote an image with N pixels that needs to be separated into c clusters, where Xi represents feature data. The algorithm is an iterative optimization process that aims to minimize the cost function, which is defined as:

(7) $J = \sum Nj = 1 \sum Ci = 1\ uijm\ ||xj - vi\ ||$^2

Here, the summation is over all N pixels and all c clusters, uij represents the degree of membership of pixel j to cluster i, and vi represents the centroid of cluster i. The cost function measures the similarity between each pixel and its assigned cluster centroid. The algorithm iteratively updates the membership degrees and cluster centroids until convergence is achieved.

In the FCM algorithm, the probability is determined based on the distance between each pixel and every individual cluster in the feature domain. The membership functions and cluster centers are updated through the following process:

1. Initialization: Set the number of clusters (c), the fuzziness parameter (m), and the initial cluster centers (u).
2. Membership Function Update: Calculate the membership value of each data point for each cluster using the following equation:
3. membership value of point i to cluster j = 1 / sum of (distance from point i to all clusters / distance from point i to cluster j) ^(2/(m-1)) where distance from point i to cluster j is the Euclidean distance between the data point i and the cluster center j.
4. Cluster Center Update: Calculate the new cluster center for each cluster using the following equation:
   new cluster center of cluster j = sum of (membership value of point i to cluster j) ^m * point i / sum of (membership value of point i to cluster j) ^m
5. Check for Convergence: Calculate the objective function J, which measures the total distance between the data points and the cluster centers weighted by the membership values. If J does not change significantly between iterations, the algorithm has converged.
6. Repeat steps 2-4 until convergence.

The membership functions and cluster centers are updated in each iteration of the FCM algorithm until convergence. The membership functions determine the degree of association of each data point with each cluster, and the cluster centers represent the mean value of all data points associated with the corresponding cluster [20].

This paper utilizes an algorithm for morphological operations based on set dilation. The result is that the target region is converted to binary 1, while the rest of the image is converted to 0. This step is more powerful than other techniques as it can modify and improve the visual features of an image. Dilation involves convolving a structuring element with the input image. The structuring element is a small binary image that defines the shape and size of the dilation operation. For each pixel in the input image, the dilation operation replaces the pixel value with the maximum pixel value within the neighborhood defined by the structuring element. This has the effect of expanding bright regions and filling in dark regions in an image.

Figure 5 depicts the RDM image after being segmented using the FCM clustering algorithm and applying morphological operations based on set dilation. The image has been partitioned into several regions based on the range and Doppler information of each pixel. Each region is assigned a unique label that distinguishes it from the other regions. The segmentation results demonstrate the effectiveness of the C-mean clustering algorithm in accurately grouping the pixels into clusters based on their similarity. This information can be further analyzed to identify and track targets in the radar image.

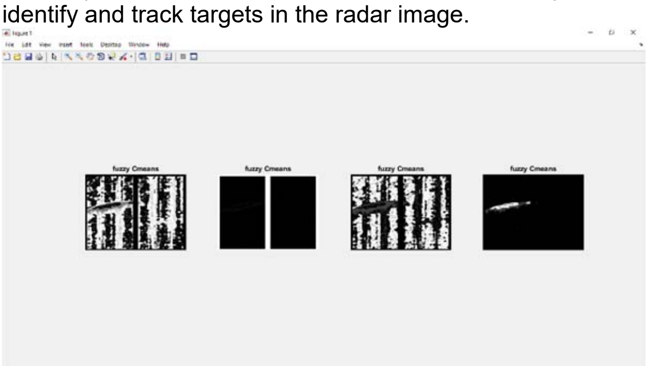

Fig.5. Segmented image Using FCM Clustering Algorithm

Feature Extraction

The GLCM was first introduced in 1973 by Haralick, Shanmugam, and Dinstein. GLCM feature extraction is a prevalent technique in image processing that involves analyzing the texture properties of an image using statistical measures derived from the GLCM. The GLCM is a matrix that summarizes the frequency of pairs of pixel intensities occurring in an image in a particular direction and distance. Various statistical measures can be derived from the GLCM to describe the texture of the image, which can be used as features for image classification or other applications [21].

The process of GLCM feature extraction typically involves the following steps:

- The GLCM is calculated based on the pixel intensities of the preprocessed image using a specified distance and direction.
- The GLCM is usually normalized to ensure that the derived features are scale-invariant and do not depend on the absolute intensity values of the image.
- Various statistical measures can be derived from the normalized GLCM to describe the texture properties of the image. Some commonly used measures include shape, color, image intensity, texture, contrast, homogeneity, correlation, and energy [22].

The selected GLCM features are then used as input to a classification algorithm, such as SVM, to classify the image into different categories.

Classification

The SVM algorithm was originally developed in 1963 by Vapnik and Lerner and is a binary classifier that employs supervised learning to provide superior results compared to other classifiers [5]. This method of classification is a form of supervised learning. SVM distinguishes between two classes by constructing a hyperplane in high-dimensional feature space, which can be used for classification purposes. SVM is an algorithm for classification that is based on various kernel methods. The concept of decision planes forms the basis for SVM. A decision plane is used to separate a group of items with differing class membership. In this study, the SVM technique was used to classify and detect target. Here are the steps involved in using SVMs to classify an RDM image:

- Data Preparation: First, the RDM image is preprocessed to extract relevant features. These features are then used as input to the SVM algorithm.
- Feature Selection: The extracted features are then selected based on their relevance to the classification task. This step is important to reduce the dimensionality of the input data and avoid overfitting.
- Training: In the training phase, the SVM algorithm uses the selected features to learn a decision boundary that separates the different classes in the data. The decision boundary is defined by a hyperplane in a high-dimensional feature space.
- Optimization: The SVM algorithm seeks to optimize the hyperplane such that the margin, i.e., the distance between the hyperplane and the closest points of each class, is maximized. This helps to ensure that the SVM model is robust to noise and can generalize well to new data.
- Classification: In the classification phase, the SVM algorithm uses the learned decision boundary to classify new RDM images based on their extracted features.

The SVM algorithm assigns a class label to the new image based on which side of the hyperplane it falls on [23].

The classification rule for SVM can be expressed as follows:

(8) $$f(x) = sign\,(\sum_i \alpha_i\, y_i\, K\,(x_i, x) + b)$$

where x is the feature vector of the RDM image, α is a vector of Lagrange multipliers obtained during training, y is the vector of class labels, K is a kernel function that maps the input data into a high-dimensional feature space, and b is the bias term.

The SVM algorithm seeks to find the values of α and b that minimize the following objective function:

(9) $$min\ ½\ ||\alpha||^2 + C\sum_i \xi_i$$

subject to:

(10) $$y_i\,(\sum_i \alpha_i\, y_i\, K\,(x_i, x) + b) \geq 1 - \xi_i$$
$$\xi_i \geq 0$$

where C is a regularization parameter that controls the trade-off between the margin and the classification error, and ξ_i are slack variables that allow for misclassifications. The SVM algorithm seeks to find the values of α and b that minimize the objective function subject to the constraints above.

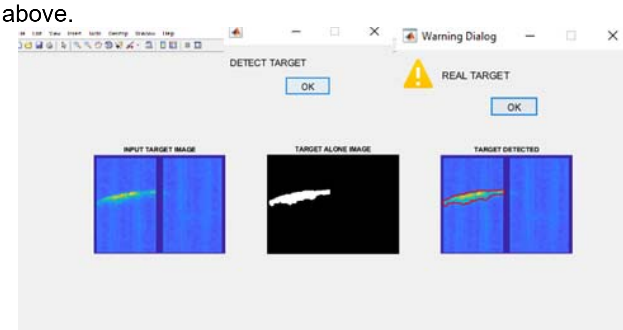

Fig.6. Target detection and classification using FCM Clustering Algorithm and SVM classifier

Fig.7. False alarm detection and classification using FCM Clustering Algorithm and SVM classifier

The SVM classifier depicted in figures 6 and 7 determines whether the target is present in the RDM image or not. In classification, the SVM algorithm assigns a test sample to a particular class based on the classification used.

Experimental Results

To evaluate the effectiveness of the proposed augmented DFB method compared to conventional DFB with the CFAR detector, a real-world flight using a Solo Quadcopter was conducted over a farm containing various objects at different altitudes such as houses, hangars, trees, grass, and cars. The UAV was equipped with a Pixhawk-2 autopilot system that includes an InvenSense MPU-6000 MEMS Inertial Measurements Unit (IMU), a U-Blox GPS, and an MS5611 barometer, which were used for positioning and localization. The radar was mounted on the underside of the UAV and tilted at a 60-degree angle towards the ground to detect ground scatters. The flight path consisted of 18 waypoints and lasted for a total of 393 seconds, with a maximum speed of 5m/s, as shown in Figure 8.

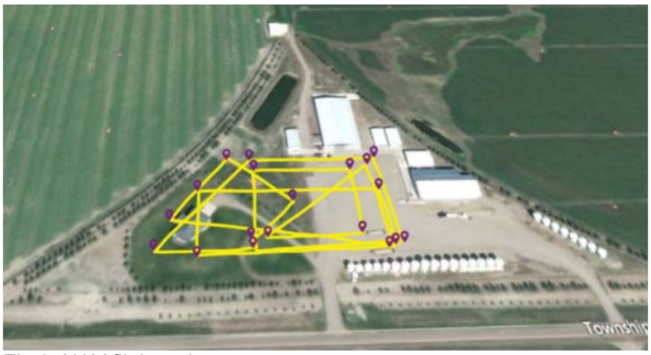

Fig.8. UAV flight trajectory

The CFAR technique is commonly used for detecting radar targets by distinguishing relevant information from background noise. It works by dynamically estimating the threshold power level and identifying targets when the echo signal exceeds it. In this approach, the power of the CUT is compared with the power of its surrounding cells (background). Although CFAR is a useful method for many applications, including airborne and ground-based radars, it is not suitable for the proposed system as it is unable to differentiate ground scatters from RDMs due to their similar power levels. An illustration of CFAR-detected targets in the RDM image is presented in Fig. 9, where some of the ground objects have been detected while others have been missed.

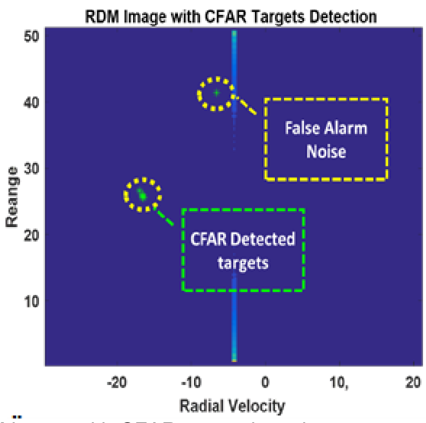

Fig.9. RDM image with CFAR target detection

Furthermore, CFAR encountered a significant false target (noise) with a high power level relative to its background. The first obstacle arises when estimating the power level of the CUT from areas with actual ground scatter while inside a CUT area with a surrounding background. Because the CUT's power level is identical to its neighboring cells, CFAR fails to detect all targets in this situation. The second issue arises due to random noise with a relatively high power level compared to its local neighborhood. To address these challenges in complex and noisy environments, an alternative system based on ML algorithms (Augmented DFB) has been proposed, unlike CFAR, which relies on local neighborhood cells to detect targets.

In this paper, SVM technique with FCM Clustering is used for segmentation and classification of RDM images. Real data set of 510 RDM images have been used to detect 'target' and 'false alarm'. The RDM images are segmented with FCM Clustering algorithm and Morphological operations and gray level co-occurrence matrix for feature extraction. The SVM classifier is trained using 450 RDM images, after that the remaining 60 RDM images was used for testing the trained SVM. Once the SVM is trained, the classification accuracy is validated using the testing set.

The texture analyses for the samples have been performed, and their values are tabulated in table 1.
From the table1 it has been inferred that the feature values obtained from the sample images are well within the acceptable range present in the literature.

Table 1. Textural features analysis for three samples of RDM images

samples	Sample1	Sample 2	Sample 3
contrast	0.2401	2.9354	1.3548
correlation	0.8822	0.4905	0.8086
Energy	0.3180	0.2487	0.3071
Entropy	1.3967	1.6784	1.4559
Homogeneity	0.9475	0.7959	0.9215
Variance	51.4554	32.7890	38.7397
Dissimilarity	0.1308	0.8762	0.3597

Table.2 provides a comparison of accuracy for SVM Kernel functions classifier result. The results demonstrate the ability of the proposed system to detect target from background noise. From the Table 2 and it has been concluded that the accuracy is in high range with linear SVM Kernel function classification when compared to Quadratic and Polynomial SVM Kernel function classification, which reveals that proposed method works well for all the images.

Table 2. CLASSIFICATION PERFORMANCES OF THE SVM CLASSIFIER

No.	SVM classifier result	
	Kernel function	accuracy
1	Linear	92.879%
2	Quadratic	82.538%
3	Polynomial	86.927%

Conclusion

Target detection is an essential part of modern radar. This paper proposes an alternative system to replace an important processing part of conventional radar signal processing hypothesis testing. The main aim of the proposed system is to enhance the probability of detection by improving the accuracy of detected targets in high-clutter environments over the conventional DFB with the CFAR detector. This goal has been achieved by employing a series of algorithms such as FCM, GLCM, and SVM. SVM proved to be a robust classifier for binary classification, achieving high accuracy and outperforming other classifiers in some cases. GLCM provided useful texture information and was able to discriminate between different land cover types. FCM was effective in segmenting the image into distinct regions based on spectral similarity. The proposed combination of these three methods provided a comprehensive approach to target extraction that takes into account both spectral and spatial features. The results showed that this hybrid approach was able to accurately extract targets from the imagery, even in complex environments with high levels of noise and variability. The experimental results demonstrate the proposed system's enhancing the accuracy rate of target detection to 92.879%.

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