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Moving Target Detection using Deep Learning

Praveena.P [1] | Sujatha.B[2] | Leelavathy.N[3]

[1]Department of Computer Science and Engineering, Godavari Institute of Engineering and Technology, Rajahmundry, Andhra Pradesh, India. praveenareddy1111@gmail.com
[2]Department of Computer Science and Engineering, Godavari Institute of Engineering and Technology, Rajahmundry, Andhra Pradesh, India. birudusujatha@gmail.com
[3]Department of Computer Science and Engineering, Godavari Institute of Engineering and Technology, Rajahmundry, Andhra Pradesh, India. drnleelavathy@gmail.com

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ABSTRACT

This study introduces a novel approach, the Deep Convolutional Neural Network-enabled Neuro-Fuzzy System (DCNN-NFS), to robustly detect moving targets in radar signals. Challenges in existing methods, such as BF-MTD and FBF-MTD, are addressed by leveraging advanced techniques like STFT, MF, radar signatures, and the newly proposed DCNN. The primary focus is on accurate pinpointing of target locations in cluttered backgrounds. The methodology includes radar signal simulation, STFT, MF, and the integration of DCNN and neuro-fuzzy systems for efficient detection. The calculated radar signatures contribute to training Deep Recurrent Neural Networks (DRNN). By combining these techniques, the proposed approach aims to overcome limitations in existing models and offer a comprehensive solution for moving target detection in radar signal processing.

Keywords: Neural Network, Convolutional Neural Network, Deep Recurrent Neural Networks

1. INTRODUCTION

Moving Target Detection (MTD) stands as a crucial discipline for identifying and tracking objects in various scenarios. Its significance spans multiple sectors, including national security, surveillance, law enforcement, search and rescue, traffic management, aviation and maritime safety, environmental monitoring, industrial automation, and technological innovation. Particularly within radar and surveillance technologies, MTD plays a pivotal role due to its wide-ranging utility and fundamental implications.

The challenge of detecting moving targets within synthetic aperture radar (SAR) signals is intricate, compounded by the presence of stationary objects contributing to signal clutter. SAR's attributes, such as all-weather capability, high-resolution imaging, multi-target tracking, and obstacle penetration, underscore its essential role in achieving accurate and reliable moving object detection.Deep learning techniques, specifically Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) elevate the proposed approach's capabilities. The deep

CNN (DCNN) excels at recognizing patterns in radar imagery, facilitating target attribute identification, while the RNN captures temporal changes, enabling trajectory tracking. This fusion of deep learning methodologies enhances the system's capacity to discern complex moving targets, augmenting robustness and versatility.Incorporating a Neuro-Fuzzy Bayesian (NFS) classifier represents the next step in enhancing moving object detection. This hybrid approach combines fuzzy logic and Bayesian reasoning, proficiently addressing uncertainties and complex relationships within radar signals. The classifier adapts intelligently, considering dynamic and uncertain radar signals, blending Bayesian insights with fuzzy logic's interpretability.

Presenting a novel MTD approach that integrates Bayesian Fusion, deep learning techniques, and a Neuro-Fuzzy Bayesian classifier to achieve robust and accurate results. The evaluation of this approach includes key metrics such as detection time (DT), Missed Target Rate (MTR), and Mean Squared Error (MSE), providing a comprehensive understanding of the capabilities. This approach demonstrates impressive adaptability across diverse scenarios involving varying target densities, iterations, pulse repetition levels, and antenna velocities. Through meticulous analysis of strengths and limitations, the MTD approach emerges as a powerful and versatile tool, poised to significantly enhance moving target detection capabilities across critical domains.

2. LITERATURE REVIEW

A review of literature on moving target detection encompasses an exploration of research, methodologies, and advancements in the field of identifying and tracking moving objects within various contexts, such as surveillance, robotics, autonomous vehicles, and more. The goal of such a review is to provide an understanding of the evolution of techniques and technologies used for detecting moving targets. Various researchers have made significant contributions to the field of moving target detection, each with distinct approaches and findings:Chen et al. [1] introduced a radar system's filter-based strategy, capitalizing on distinct Doppler frequency shifts due to varied velocities. This approach is vital in moving target detection, crucial in tasks like localization, tracking, and identification.Li et al. [2] emphasized that intricate detection conditions and diverse target motion lead to nonstationary radar echo signals. While Fourier transform (FT)-based moving target detection excels with uniform motion, it struggles with rapidly maneuvering targets due to spectrum divergence and energy accumulation challenges.

In the work of Fang, Z. Cao et al. [3], the time-frequency analysis (TFA) approach emerges as a robust tool for probing nonstationary signals, unveiling an extensive signal distribution panorama across the time-frequency plane. This methodology entails extracting target-specific attributes from the Time-Frequency (TF) domain to streamline moving target detection. Incorporating techniques like short-time Fourier transform (STFT), fractional Fourier transform (FRFT), Wigner–Ville distribution (WVD), and Choi–Williams distribution (CWD), this approach heightens real-time responsiveness and obviates the need for pre-established motion parameter information.Su, X. L. Chen, J. Guan [4] employed the STFT to derive TF images of echo signals from sea surface moving targets. They harnessed three distinct CNN models—LeNet, AlexNet, and GoogleNet—for binary detection and multiple micromotion classifications. The efficacy of these methods relies significantly on the echo signal model and the TFA technique, both of which exert direct influence over target detection accuracy.

In the study by Xing M. D. and Bao Z. [5], the previously mentioned methodologies grapple with issues surrounding signal modeling, TF resolution, and noise robustness. To illustrate, attempting to represent the echo signal from high-speed maneuvering targets using an equal amplitude linear frequency modulation (LFM) signal model comes with inherent limitations. Moreover, opting for a fixed window function within the STFT compromises the simultaneous achievement of high temporal and frequency resolutions. Shui P.L and Shang H.Y et al. [6] addresses the task of estimating Doppler parameters for moving targets. However, when employing WVD-based algorithms, a notable complication arises due to the generation of cross-terms, particularly in scenarios with multiple moving targets [3]. In these intricate scenarios, the fractional Fourier transform (FrFT) proves to be a valuable remedy.

Zhongyu Li et al. [7] introduced a novel technique that combines coherent and non-coherent integration of received signals within the fractional Fourier transform (FrFT) domain.H. B. Sun and team [8] emphasized the underexplored potential of the FrFT in radar signal processing, particularly for efficient aerial SAR ground moving target identification. In a similar manner, S. Baumgartner et al. [9] proposed a knowledge-based approach for ground moving target indication (GMTI) and parameter estimation in SAR, suitable for real-time aerial traffic monitoring applications.Eppili. Jaya [10] aimed at precise and effective moving object identification using SAR technology. They built their MTD approach upon the foundations of the FrFT and adaptive-neuro fuzzy decision techniques.A. Taylor et al. [11] stressed the significant role of coherence between received signals in the successful detection of moving targets using multichannel synthetic aperture radar (MSAR). In their studies, differences in coherence were shown to impact detection capabilities.

Liu etal [12] demonstrated effective clutter suppression using adjacent pixel information in both joint pixel and signal subspace projection approaches. Experimental results favored the joint pixel approach for clutter suppression.Shifting focus to Bayesian learning, Nair S. et al. [13] applied this technique to multiple target detection, updating belief maps and realigning targets based on these maps. Churesampani K. et al. [14] explored the fusion of multi-temporal SAR data and optical data using a Bayesian technique for land cover classification. It is evident from the diverse studies mentioned that the FrFT holds promise in various radar and signal processing applications, particularly in the realm of MTD and classification.

Yu, G., Piao, S. et al [15] introduced the utilization of the Fractional Fourier Transform (FrFT) in SAR signals, demonstrating its advantages over the conventional matching filter bank approach. This approach has been found to exhibit reduced bias and enhanced robustness. Tsyganskaya et al., [16] extended this fuzzy logic methodology not only tackles the complexities stemming from the ambiguity of SAR signatures but also delivers reliable results by means of data training.Zadeh and Mendel [17] proposed a fuzzy system for evaluating the confidence in information from gated blobs and predicted tracks. This involves using numerical heuristics to define attributes for each scenario. When expert knowledge is unavailable, automated learning can determine membership functions and fuzzy rules for linguistic variables.Lee and Lee [18] introduced a highly efficient DL-based method tailored for real-time computation on small unmanned aerial vehicles with limited space, showcasing its effectiveness.An et al. [19] introduced an enhanced rotating bounding box coding scheme coupled with a Convolutional Neural Network (CNN) to address detection target imbalances, demonstrating improved outcomes compared to standalone components. Zhang and Zhang [20] amalgamated image recognition technology with athlete motion recognition, addressing foreground image anomalies through morphological operators to enhance recognition precision.LeCun Y. et al. [21] pioneered the integration of CNNs as a fundamental component in target detection algorithms, specifically for candidate region analysis. With its local connectivity and weight sharing advantages, CNNs exhibit robustness in object classification applications.Van Uijlings et al. [22], target detection algorithms that utilize region proposals generate candidate regions potentially containing objects. These algorithms commonly utilize techniques such as selective Search and edge boxes. The final results are achieved through subsequent testing and verification of these candidate regions. Zhou et al. [23], emphasized the heightened significance of target recognition ability in intricate scenes involving multiple identifications and processing. The study centers on advancing moving target recognition methods via deep convolutional neural networks. By analyzing and contrasting research efforts, it outlines the current state and offers prospective research directions for moving target recognition.

Xu and Wang et al introduced R-CNN [24] model, marked a significant advancement in target detection. Uan Tang et al. emphasized the importance of configuring the network's basic units. Modifying width and depth aids parameter adaptation and mitigates overfitting [25]. Addressing variable target sizes in surveillance media necessitates using three convolutional layers with distinct kernel sizes for feature extraction.Chen et al. [26] highlighted a method using a 5-layer convolutional neural network for moving target detection. The statistical learning-based recognition algorithm exhibits adaptability and effectiveness, yet demands abundant samples, higher processing power, and longer operation time.Li Qin [27] presented a moving target recognition approach using deep convolutional neural networks (DCNN) to extract target features. When the network is shallow, its recognition capacity might lag behind conventional SVM and boosting methods. Conversely, with a deeper network, substantial training data is required to avert overfitting during learning.

Wang and Huang et al. [28] introduced a DCNN method for recognizing moving target behaviors, offering powerful modeling capabilities. Through supervised, semi-supervised, or unsupervised training, it enables layer-by-layer feature learning and automatic abstraction of object hierarchy.Li Zhongyu et al. [29], proposed a multi-frame fractional Fourier transform technique for detecting moving targets with space-based passive radar. This method addresses the challenge of low power density from satellite transmitters, requiring longer integration times to enhance the signal-to-background ratio.Conte et al [30] address radar detection of coherent pulse trains in spherically invariant noise with unknown statistics. They propose a new detector using an estimated covariance matrix from secondary data vectors, achieving a steady false alarm rate while accommodating a loss in performance compared to a known covariance matrix scenario. The study deals with adaptive matched filter detection.

Yu G, and Han et al. [31] put forth a technique employing FrFT for the detection and estimation of delay times for moving targets. LFM signals are chosen as the transmitted signals owing to their sensitivity to Doppler shift and ability to achieve high range resolution.Huajian Xu et al. [32] proposed a shadow-aided technique for enhancing ground moving target indication (GMTI) in multichannel high-resolution synthetic aperture radar systems. The approach introduces geometric relationships and a multi-feature fusion-based shadow detection method, showcasing superior results in numerical simulations compared to traditional methods.Tschichold-Gürman et al [33], introduced neuro-fuzzy systems (NFS) neural network-based methods often presented as multilayer feedforward neural networks. In recent times, the NFS has garnered heightened attention within research communities, surpassing other variants of fuzzy expert systems. This surge in interest can be attributed to its unique amalgamation of NN learning capabilities and FL reasoning prowess. This combination enables the NFS to adeptly address numerous intricate and nonlinear real-world challenges with a remarkable level of accuracy.

3. SIGNAL MODELLING IN MTD

Signal modeling in MTD is of paramount importance in the domain of radar technology, particularly within applications like SAR systems. This process involves creating mathematical representations of radar signals to extract crucial information about moving objects.The SAR used for surveillance application requires the capabilities to detect targets using sensing data and subsequently optimizing the placement of objects for efficient sensor coverage within the sensing range. According to [5], the Linear Frequency Modulated (LFM) wave is given by

$$z_y(t,\ \vartheta) = rect\,(\vartheta|p) \cdot \exp\,\left(j\pi \cdot \phi\,\vartheta^2\right) \cdot \exp\,\left[j2\pi f_c\,(t+\vartheta)\right] \tag{1}$$

where, " p " represents the average PR time, " t " corresponds to slow time component, carrier frequency "fc," and "r" indicates the time it takes for the signal to travel to the target and return. The rectangular function can be described by

$$rect() = \begin{cases} 1; & |u| \leq \frac{1}{2} \\ 0; & \text{Otherwise} \end{cases} \tag{2}$$

Additionally, the slow time of the LFM waveform experiences variation in accordance with the subsequent equation:

$$t = \left[v + \rho\left(v'\right)\right] u;(c = 0, 1, \ldots, C) \tag{3}$$

Where "C" designates the total integrated pulses and "c" represents specific range index being considered which is expressed as

$$c' = \bmod\,(c,\ G) + 1\,; G(G < C) \tag{4}$$

The expression for the baseband signal within the context of SAR can be articulated as follows:

$$z(t,\ \vartheta) = \gamma\,E\ \sin e\left[\pi \cdot \beta\left(\vartheta - 2\,K(t) \times \frac{1}{e}\right)\right] \cdot \exp\left[-j4\pi K(t) \times \frac{1}{\lambda}\right] \tag{5}$$

In addition, another element contributing to the modeling of SAR signals is the instantaneous slant range $K(t)$ as:

$$K(t) = K_0 - b_0 \cdot t - j_0 \cdot \frac{t^2}{2} \tag{6}$$

The equation (5) is reconfigured the substitution of equation (6) to yield:

$$\begin{aligned} z(t,\vartheta) = \gamma E \operatorname{sin} e &\left[\pi \cdot \beta\left(\vartheta - 2\left(\left[K_0 - b_0 \cdot [c + \rho(c')]\, v - j_0 \cdot \frac{[[c+\rho(c')]\, v]^2}{2}\right]\right) \times \frac{1}{e}\right)\right] \\ &\times \exp\left[-j4\pi \frac{K_0}{\lambda}\right] \times \exp\left[\left(j4\pi \cdot b_0 \cdot mr + \frac{j_0\,(cv)^2}{2}\right) \times \frac{1}{\lambda}\right] \\ &\times \exp\left[j4\pi \times \left(b_0\, \rho(c') \cdot v + b_0\left[2c\rho(c')\, r^2 + [\rho(c')v]^2 \times \frac{1}{2}\right]\right) \times \frac{1}{\lambda}\right] \end{aligned} \tag{7}$$

The depicted equation characterizes the oscillating signal envelope, which is influenced by variables such as radial acceleration and radial velocity. The SAR signal experiences decomposition due to altering frequency offset conditions, and its mathematical depiction is as follows:

$$\varepsilon_1 = \exp\left\{ j4\pi\left(b_0 \cdot cv + \frac{j_0\,(cv)^2}{2}\right) \times \frac{1}{\lambda}\right\} \tag{8}$$

$$\varepsilon_2 = \exp\left\{ j4\pi\left[b_0 \cdot \rho(c')\, r + j_o\left[\left[(2c\,\rho(c'))\, r^2 + (\rho(c')\, v)^2\right] \times \frac{1}{2}\right]\right] \times \frac{1}{\lambda}\right\} \tag{9}$$

The above expressions (8) & (9) indicate variations due to oscillation parameters and their alteration.

4. PROPOSED METHOD OFDCNN-NFS FOR MTD

This section introduces the approach of using a deep CNN-based neuro-fuzzy system for detecting moving targets. Figure 1 illustrates the process of detecting moving targets using the proposed DCNN-NFS. The detection of these targets relies on analyzing the signal transmitted within a specific range. The signal that bounces back from the target is treated as the received signal, which serves as input for the target detection process. This received signal undergoes processing through various steps including short time Fourier transform (STFT), matched filter (MF), and radar signatures-based deep recurrent neural networks (DRNN), and the proposed DCNN to generate an ambiguous function.Additionally, specific radar signatures such as PRI, PD, CF, AAE, EAE, and DE are extracted from the received signal. These extracted signatures are then used as input for the DCNN to accurately detect the location of the targets. Through the analysis of the generated AFs, both correlation values and maximum energy are computed to effectively pinpoint the targets' locations.Finally, the results indicating the target locations are fed into the NFS, which plays a crucial role in accurately detecting the moving targets. This comprehensive approach enhances the overall efficacy of moving target detection.

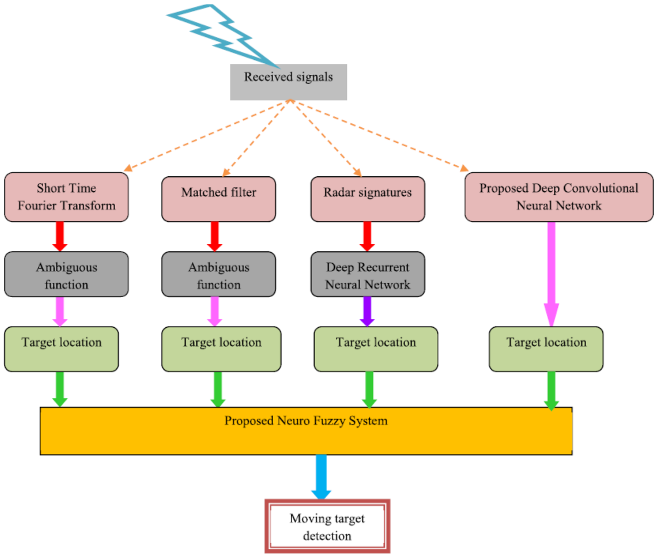

Figure 1: Schematic diagram of the proposed DCNN-NFS for MTD.

Matched Filter - The Matched Filter (MF) exploits the known characteristics of the transmitted radar pulse and the expected Doppler shift caused by moving targets to improve the signal-to-noise ratio and detect weak moving targets in the SAR data. The MF correlates the received radar returns with the time-reversed complex conjugate of the transmitted pulse. After the MF operation, the output contains enhanced signals from the moving targets, making them more distinguishable from clutter and noise. It is particularly effective for detecting slow-moving or weak targets in SAR data.Detection algorithms can then be applied to the filtered data to identify and localize the moving targets.The ratio of powers of signal to noise is given by

$$\left(\frac{SP}{NP}\right)_{out} = \frac{|S_0 t_0|^2}{{n_0}^2\,(t)}. \tag{10}$$

Where, SP= Signal Power, NP = Output Noise Power, S (t_0) = Value of signal at t = t_0 and ${n_0}^2\,(t)$ = mean square value of noise

Applied Matched Filter to the received signal - Once STFT is obtained, matched filter is applied. The MF and Ambiguous Filter helps in detecting. Matched filter identifies the shifted signals makes the process more effective. AF is two – dimensional. The delay signal and Doppler frequency are related. It also gets the correlation between P and time distorted Doppler signal. Time response of filter is measured as it refers to the signal arriving with delay & shift. Application of AF to matched filter is given:

$$S(\vartheta,f) = \frac{1}{|S(0,0)|}\int_{-\infty}^{\infty} P(t).P^{*}(t+\vartheta).e^{j2\pi ft}\,dt \tag{11}$$

$$S(0,0) = \int_{-\infty}^{\infty} |P(t)|^{2}dt \tag{12}$$

Where S(0, 0) is related to normalizing in the received signal. Further identification of time shift by matched filter is done by

$$\int_{-\infty}^{\infty} P(s).P^{*}(t+\vartheta).e^{j2\pi ft}\,dt \tag{13}$$

Ambiguity Function - Ambiguity Function is a two-dimensional function that represents the correlation between the transmitted radar pulse and the received radar return as a function of time delay and Doppler frequency. It provides valuable insights into the Doppler shift induced by moving targets and the time-delayed echoes from stationary and moving scatterers. It helps to develop effective algorithms for MTD and compensation of motion-induced distortions in SAR imagery.When the radiation of signalling is done, sufficient time passes for return of echo prior to next radiation. When the time gap is less, echo may arrive after the next pulse in case of high range. Maximum unambiguous range can be expressed as

$$R_{un} = C\,T_{P} / 2 \tag{14}$$

Here T_P gives the time of pulse repetition.

4.1 Estimation of Correlation Using Maximum Energy

Correlation Function - The correlation function is a technique used to measure the similarity between two signals, such as the transmitted radar pulse and the received radar return. In the context of moving target detection in SAR, the correlation function is used to compare the received radar signals at different time instants and identify the Doppler shift caused by moving targets.

Maximum Energy Function -It measures the energy content of the received radar signals at different Doppler frequencies and identifies the frequency bin with the maximum energy. This frequency bin corresponds to the Doppler frequency shift caused by the moving target

Correlation estimation through maximum energy - Next step is the identification of correlation by both STFT & matched filter responses. The principle is based on maximum energy. For correlation, the expression is:

$$A(\vartheta,P) = \frac{1}{|A(0,0)|}\int_{-\infty}^{\infty} P(t).P^{*}(t+\vartheta).e^{j2\pi f(t+\vartheta)}\,dt \tag{15}$$

Where $P^{*}(t + \vartheta)$ gives shifting. Other than AF, correlation is applied to STFT as

$$Cor^{STFT}(\vartheta,P) = \frac{1}{|Cor^{STFT}(0,0)|}\int_{-\infty}^{\infty} R_{\sigma}[a](g)R_{\sigma}^{*}[a](g).e^{j2\pi f(t+\vartheta)}\,dt \tag{16}$$

Where $Cor^{STFT}(\vartheta,P)$ gives maximum energy for finding the target.

5. DEEP CNN FOR THE RECEIVED SIGNAL

CNN is employed to process the received signal data for the purpose of detecting moving targets. The CNN is designed to automatically learn and extract relevant features from the input signal, using layers of convolutional, pooling, and a fully connected (FC) layer with activation functions (AF). These learned features enable the network to discern patterns and variations indicative of moving targets, facilitating accurate detection and classification in applications such as radar, sonar, or other sensor-based systems [25]. The proposed DCNN model is shown in Figure 2.

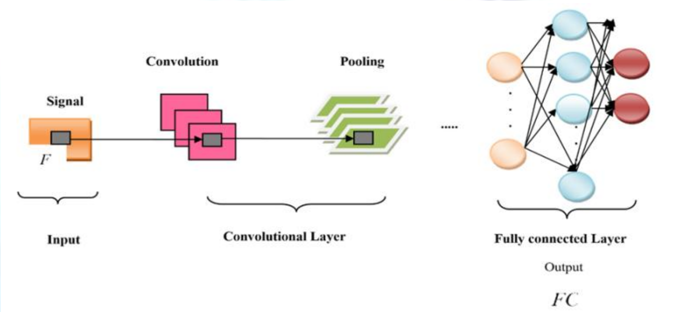

Fig.2: Structure of Deep CNN.

The Deep CNN plays a pivotal role in processing compressed signals for MTD, comprising three layers: convolutional (CONV.) for feature mapping, pooling (POOL) for feature map sub-sampling, and a fully connected (FC) layer for final detection. These layers collectively function as follows:

Convolution layers: The purpose of these layers is to identify patterns in the compressed signal using CONV filters when input F is processed through the DCNN, it produces an output.

$$\left(F_{v_i}^{\;s}\right)_{x,y} = \left(D_{v_i}^{\;s}\right)_{x,y} + \sum_{\alpha=1}^{F_1^{\alpha-1}} \sum_{\psi=F_1^{s}}^{F_1^{s}} \sum_{\sigma=F_2^{s}}^{F_2^{s}} \left(\theta_{v_i,\alpha}^{\;s}\right)_{\sigma,\psi} * \left(F_{\alpha}^{\;s-1}\right)_{x+\psi,\,y+\sigma} \tag{17}$$

- Pooling Layers:Being non-parametric, these layers operate without biases or weights, ensuring efficient and effective performance.
- Fully Connected Layers:The output signal from the pooling layers serves as input for the FC layer, where multiple signals are combined into

a single signal representing the signal's class, yielding the final output. The resultant output is given by:

$$FC_{v_i}^{s} = \varpi\left(F_{v_i}^{s}\right) with\ \ F_{v_i}^{s} = \sum_{\alpha=1}^{F_1^{\alpha-1}} \sum_{\psi=F_1^{s}}^{F_1^{s}} \sum_{\sigma=F_2^{s}}^{F_2^{s}} \left(\theta_{v_1,\alpha}^{s}\right)_{\sigma,\psi} \left(F_{v_i}^{s-1}\right)_{x+\psi,\, y+\sigma} \tag{18}$$

The output of DCNN, signified as FC, is computed for locating the targets based on the vector C_f.

6. TRAINING PHASE PROPOSED NFS ARCHITECTURE FOR MTD

The Neuro-Fuzzy system (NFS) for moving target detection combines the advantages of Fuzzy logic (FL) and neural networks (NN) to enhance the accuracy and efficiency of detecting moving objects. The proposed system integrates outputs from different techniques, such as STFT, MF, DRNN, and DCNN, using a fusion approach inspired by Tschichold-Gürman[33].

The training procedure involves optimizing various parameters through fuzzification, normalization, defuzzification, and summation stages. Fuzzification employs membership functions to capture fuzzy clusters from input values, determining firing strengths based on membership values [34]. Normalization calculates firing strengths in relation to rates, providing a normalized ratio of firing strength to rule, contributing to the overall firing strength. The defuzzification layer computes weighted values, while the summation layer combines the results for output generation.

The training process of the NFS is explained here. The fuzzy inference system comprises two inputs and one output. Let's denote the two inputs as "a_i" and "c_i," and the output as "c_i." The Sugeno fuzzy (SF) model [35] is utilized to methodically derive fuzzy rules from the dataset, considering the interactions between input and output.

The 1st order SF inference system with two rules is expressed as follows:

$$\text{Rule 1 : If } a_i \text{ is } X_1 \quad \text{and} \quad b_i \text{ is } Y_1, \quad \text{then } F_1 = l_1$$

$$\text{Rule 2 : If } a_i \text{ is } X_2 \quad \text{and} \quad b_i \text{ is } Y_2, \quad \text{then } F_2 = l_2$$

The output c_i is generated from the input vector (a_i, b_i).

where firing strengths are represented by α and β, generated through the multiplication of membership grades. The weighted average of output rules is indicated by δ. The functions of nodes within each layer are as follows:

Layer 1: Each node represents a square node with the function

$$N_r^1 = \gamma_{X_r}(a_i) = \frac{1}{1 + \left|\frac{a_i - z_r}{e_r}\right|} \tag{19}$$

where, "a" signifies the input to node "r," and "Xr" corresponds to the linguistic label associated with the node function

Layer 2: Firing strength of a rule is computed through multiplication.

$$N_r^2 = o_r = \gamma_{X_r}(a_i).\gamma_{Y_r}(b_i); \quad r = 1, 2 \tag{20}$$

Layer 3: Node r calculates the ratio of a rule's firing strength to the overall firing strength.

$$N_r^3 = \overline{o_r} = \frac{o_r}{o_1 + o_2}, \quad r = 1, 2 \tag{21}$$

Layer 4: Node ϕ determines the contribution of a rule to the overall output.

$$N_r^4 = \overline{o_r} C_r = \overline{o_r}(l_r a_i + h_r b_i + g_r) \tag{22}$$

Layer 5: The final output is computed as a linear combination of resulting parameters.

$$N_1^5 = \sum_r \overline{o_r} F_r = \frac{\sum_r o_r F_r}{\sum_r o_r} \tag{23}$$

The overall output "C" can be expressed as a linear combination of the resultant parameters.

$$C = (\overline{o_1} a_i) l_1 + (\overline{o_1} b_i) h_1 + (\overline{o_1}) g_1 + (\overline{o_2} a_i) l_2 + (\overline{o_2} b_i) h_2 + (\overline{o_2}) g_2 \tag{24}$$

Thus, the training process for NFS is illustrated below as follows,

Step 1: Find the error caluclation $h_n : \dfrac{\sum_{i=1}^{t} [h_n(x_i) \neq y_i]}{t}$

Step 2: If $\sum_n = \gamma$, then drop hypothesis and divide DS_j into k subsets $S_1, S_2, ... S_k$

Step 3: Estimation of normalized error, $\tau_n = \dfrac{\epsilon_n}{1 - \epsilon_n}$, $0 < \tau_n < 1$

Step 4: Then, the weights are indicated as, $w_n = \log \dfrac{1}{\tau_n}$

Step 5: Update operation is done,

$$z_{n+1}(i) = z_n(i)\begin{cases} \tau_{nn}, if\ h_n(x_i) = y_i \\ 1, if\ h_n(x_i) \neq y_i \\ \gamma, if\ h_n(x) \neq y_i \end{cases}$$

Step 6: As a result, composite hypothesis is described as,

$$H_j^m = \arg\ mean \sum_{n=1}^{t} \log \frac{1}{\tau_n^m}$$

Thus, the detection of moving targets is carried out using the fuzzy system and is denoted as H_j^m. The major benefit of this technique is to minimize the time of computation, and also for enhancing the training performance.

7. RESULTS & DISCUSSION

This section conducts an empirical analysis of simulation results derived from the implementation of the DRNN-FBF model. Validation of the proposed DRNN-FBF model's effectiveness is accomplished through simulation outcomes obtained from a RADAR simulation platform, utilizing the MATLAB R2018a tool. Performance assessment is based on the evaluation metrics including DT, MTR, and MSE. This process aims to demonstrate the practical viability and efficacy of the DRNN-FBF model for moving target detection.

Table 1 provides a comparative analysis of the novel DCNN-NFS approach against existing MTD techniques, considering DT, MTR and MSE variations across different factors: no. of targets, iterations, and PRL. For a pulse repetition level of 0.003, the proposed method achieves a notably reduced detection time of 1.221 s, surpassing other techniques like FrFT (12.21 s), MF (8.553 s), multi-frame FrFT (1.880 s), Li et al.'s method (8.963 s), BF-MTD (6.904 s), FBF-MTD (3.249 s), and DRNN-FBF (2.646 s). Additionally, the MTRs for the proposed method are significantly lower (0.022) compared to existing techniques, such as FrFT (0.568), MF (0.283), multi-frame FrFT (0.071), Li et al.'s method (0.302), BF-MTD (0.227), FBF-MTD (0.052), and DRNN-FBF (0.049).

Moreover, the proposed deep CNN-based neuro-fuzzy system attains a notably reduced MSE of 1,952.15, while existing techniques yield higher MSE values: FrFT (55,741.74), MF (52,861.73), multi-frame FrFT (74,778.09), Li et al.'s method (54,239.93), BF-MTD (12,701.96), FBF-MTD (5,073.24), and DRNN- FBF (3,438.20). The results affirm the superior performance of the proposed approach across all evaluated parameters.

The results from Table 1 underscore the superiority of the proposed DCNN-NFS, showcasing its advantages in terms of minimal detection time (1.221s), reduced missed target rate (0.022), and lower MSE (1952.15) for the given pulse repetition level.

Table 1: Comparative discussion of the developed DCNN-NFS method

Variation	**Metrics**	**FrFT [31]**	**Matched filter [30]]**	**Multi-frame FrFT [32]**	**Li et.al [29]**	**Proposed DCNN-NFS**
Varying number of targets -20	Detection time (secs)	12.88	12.01	12.63	12.09	1.49
	Missed target rate	0.681	.556	0.536	0.578	0.030
	MSE	62418.97	51666.98	87602.47	53013.08	1250.66
Varying number of iterations -20000	Detection time (secs)	11.69	11.40	14.40	11.14	1.53
	Missed target rate	0.412	0.259	0.634	0.261	0.036
	MSE	54728.75	44536.71	77417.07	42101.48	2020.56
Varying pulse repetition level- 0.004	Detection time (secs)	12.21	8.553	1.880	8.963	1.221
	Missed target rate	0.568	0.283	0.071	0.302	0.022
	MSE	55741.74	52861.73	74778.09	54239.93	1952.15
Varying antenna turn velocity-3.1416	Detection time (secs)	11.0347	8.4567	9.5139	6.9638	1.357
	Missed	0.4975	0.3908	0.4143	0.3958	0.0035

	target rate					
	MSE	58473 .75	56674 .75	43790.02	27568 .04	1625.36

8. CONCLUSIONS

In this section, a novel approach called DRNN-FBF is introduced to enhance the detection of moving targets within a RADAR system, particularly in the context of MTD in SAR research. The approach aims to address challenges posed by stationary objects causing signal scattering, which has limitations on detection capabilities despite extensive MTD studies. The proposed methodology involves combining outcomes from DRNN, STFT, FT, and MF techniques using the FBF decision model.A comprehensive evaluation, considering diverse scenarios involving varying target counts, ATV, PRL, and iteration counts, underscores the approach's efficacy. Comparative analysis against established MTD techniques, e.g., FBF-MTD versus BF-MTD, illustrates substantial enhancements—reduced DT (e.g., from 5.904 to 2.9551 seconds), lower MTR (e.g., from 0.152 to 0.0897), and improved MSE (e.g., from 5626.9 to 2683.80).Moreover, a new method, DCNN-NFS, is introduced, integrating STFT, MF, and DCNN. DCNN-NFS yields remarkable results, including DT (e.g., 1.221 seconds), minimal MTR (e.g., 0.022), and low MSE (e.g., 1952.15), all while accounting for PRL.Finally, DCNN-NFS mark significant advancement in moving target detection, offering improved accuracy and performance compared to traditional methods.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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