

We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

7,000

Open access books available

186,000

International authors and editors

200M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com



Deep Learning Network for Classifying Target of Same Shape using RCS Time Series

Rashmi Narasimhamurthy and Osamah Ibrahim Khalaf

Abstract

The main intension of this work is to find the warhead and decoy classification and identification. Classification of radar target is one of the utmost imperatives and hardest practical problems in finding out the missile. Detection of target in the pool of decoys and debris is one of the major radas technologies widely used in practice. In this study we mainly focus on the radar target recognition in different shapes like cone, cylinder and sphere based on radar cross section (RCS). RCS is a critical element of the radar signature that is used in this work to identify the target. The concept is to focus on new technique of ML for analyzing the input data and to attain a better accuracy. Machine learning has had a significant impact on the entire industry as a result of its high computational competency for target prediction with precise data analysis. We investigated various machine learning classifiers methods to categorize available radar target data. This chapter summarizes conventional and deep learning technique used for classification of radar target.

Keywords: Convolution neural organization (CNN), Recurrent Neural Network (RNN), Support Vector Machine (SVM), High Resolution Range (HRR), Radar Cross Section (RCS), Target classification

1. Introduction

Many countries have spent significant resources to countermeasure research and development in order to condense the efficacy of defense mechanism of Ballistic Missile systems. Using decoys in large number, or fake targets, to ambiguous defense systems is one of the most prevalent tactics. Various decoy tactics, such as replica decoys, signature diversity decoys, and anti-simulation decoys, are currently accessible. Because the weight of payload determines missile's warhead size and range, lightweight decoys are a very interesting choice in contrast to exo-atmospheric defenses. As a result, missiles can carry lightweight decoys in larger number without compromising the maximum range of the payload [1]. In exo-atmospheric in which mid-course phase of a BM flight occurs is the longest part of the journey. Since warhead and decoys travel on comparable trajectories due to same physics a large number of decoys are deployed in midcourse phase [2]. Missiles can release accompanying debris and hardware, such as missile launch boosters, which can cause further radar interference. Since anti-ballistic missile

systems are equipped with few numbers of interceptors, In the absence of accurate target identification, it is challenging for anti ballistic missile system to avoid the warhead from reaching its intended target The classification challenge of targets, which involves recognizing the warhead among a larger number of decoys and debris, is critical. So, the need of the hour is to have the desired classification algorithm with high efficiency, low computational complexity and swift decision times for defense radar station. Furthermore, once the target has been classified and located, the seeker on the interceptor must regulate the target location on the vehicle on re-entry for successful lethal supervision and control during the rendezvous [3]. It is crucial to highlight that decoy can have a substantial impact on the efficiency of a defense system in two ways. If a decoy is mistakenly identified as a warhead, the defense may run out of interceptor ammunition too rapidly (false alert). On the other hand, misclassification (see page) of a weapon may result in its destruction.

Because of the developed target credentialing system based on the distinct micro-motions produced by Ballistic targets, the capacity to discriminate between warheads and decoys has attracted a lot of attention in the literature. Organize their planned ballistic trajectories while demonstrating precession and parapet motion caused by the Earth's gravitational pull [3–5]. On the other hand, due to lack of spinning engine and also due to gravity decoys flip when launched by missiles [6, 7]. In order to obtain the target's micromotion, the radar signals are analyzed using Doppler and range analysis. The phenomena were first described in the Doppler domain by V. Chen in [8], and it is now known as the micro-Doppler effect. Neural network algorithms are extensively used for classification, Deep learning (DL) is a subset of a larger family of data representation-based machine learning algorithms. An observation (such as an image) can be represented in a variety of ways, such as a vector of intensity values per pixel, or more abstractly as a set of edges, specified shape regions, and so on. In [3] Convolution Neural Network (CNN) for classifying aircraft target using LeNet was presented and compared with SVM. The author [6] describes the classification of target using recurrent neural network (RNN) [9–11].

1.1 Ballistic missiles

Missile are the main threats that defense systems have been developed to fight. Initially Ballistic missiles are propelled by rockets, but eventually track the path of targets. They are categorized based on the missile range. To increase the range of a missile, rockets are piled over each other in a staging conformation.

The ballistic missiles categorized in to four categories based on the range it travels it covers:

1. Ballistic missile covering a range less than 1000 kilometers are known as Short range Ballistic missile;
2. Missiles covering a range between 1,000–3,000 kilometers are called as Medium Range Ballistic missile;
3. Ballistic missiles covering a range of 3,000–5,500 kilometers are refereed as Intermediate-range Ballistic missile;and
4. Advanced Ballistic missile covering a range over 5,500 kilometers are called Intercontinental ballistic missiles (ICBMs)

1.2 Ballistic missile launch occurs in three flight stages

Boost phase:

During boost phase missile will be launched and this phase last till the rocket shuts its engine. When rocket shuts its engine, missile is pushed away from Earth. This phase will last anywhere from three to five minutes. The missile moves slowly in general, but an advanced ICBM can achieve speeds of over 6.6 kilometers per sec. Generally this phase takes place in the air (endo-atmospheric).

Midcourse phase:

Upon successful completion of Boost phase missile enters the midcourse phase where in which the missile is over a Ballistic trajectory in the direction of its target. This phase is the longest among the three stages lasting up to 20 min for ICBM. Midcourse phase is divided into two subphases one is the rising phase where missile is moving towards its apogee, in later stage missile is moving towards the earth. During this stage, the missile's warhead(s) and any decoys disengage from the conveyance platform, or "bus." This phase takes place in exo-atmospheric. For the warhead, a reentry vehicle has been requested (RV).

Phase of completion:

The terminal phase begins when the missile's warhead reenters the Earth's atmosphere and lasts until impact or detonation. For a tactical warhead traveling at speeds of more than 0.88 kilometers per sec, this phase takes less than a minute [12].

2. Radar cross section

During the midcourse threat missiles releases its warhead and decoys together, however ground based radar begins tracking the threat in cloud of decoys. Based on the information from radar in the form of RCS returns. Ground based radar classifying using one of the several methods to classify the warhead in the pool of decoys. After classification Ground based radar launches one or more interceptor. The intercept holds kill vehicle. Kill vehicle determines which object is the warhead based on the shape of warhead, it then steers itself into the path of warhead and destroy it with the force of impact. In this section of the chapter, we define Radar Cross section of the target with different shapes. Considering Monostatic pulsed Radar. The RCS of a target is the area that the radar signal intercept.

Mathematically, it is written as:

$$\sigma = \lim_{R \rightarrow \infty} 4\pi \frac{|E_s|^2}{|E_i|^2} R^2 \quad (1)$$

Where:

R = Distance traveled by the radar signal to target

E_s = Electric field strength scattered at target.

E_i = Incident electric field strength at target.

2.1 RCS of cylinder and cone

The aspect angle, wavelength of operation and polarization are few parameters determines RCS of a target. When the dimension of the target exceeds the wavelength, the RCS of a conducting plate is approximated by σ .

The product is given by:

$$\sigma = G_e \cdot Ap = \frac{4\pi Ap}{\lambda^2} \cdot Ap = \frac{4\pi A^2}{\lambda^2} \quad (2)$$

The approximate formula for the RCS of simple cylinder and cone is given by:
Cone RCS:

$$\sigma = \frac{\lambda^2}{16\pi} \tan^4 \theta; \quad (3)$$

where θ_{cone} half angle.
Cylinder RCS:

$$\sigma = \frac{2\pi a L^2}{\lambda} \quad \text{where } a : \text{Radius; } L : \text{Length} \quad (4)$$

3. Classical techniques for radar target identification

The boost, midcourse, and reentry phases of a ballistic missile's flight can be split into three categories. The midcourse begins once the boosters have been turned off. The warhead detaches from the rocket and decoys are released. Because the midcourse may account for 80–90% of the total flight time [1, 13], identifying and intercepting the warhead is a critical phase for the BMD system. However, identifying warheads from decoys is challenging due to their nearly identical macro-motions [2]. To maintain attitude control, the warhead spins in mid-flight. The warhead's micro-motion becomes spinning and processing at a miniscule nutation angle as a result of the inevitable tumbling. After initial tumbling, Wang [3] revealed that an axisymmetric decoy's micromotion spins and processes, similar to a warhead, but with a higher nutation angle. The most difficult difficulty in this study is distinguishing between a warhead and a decoy of identical shape in mid-flight, with the sole difference being micro-motion.

In radar target recognition, there are a plethora of ways (RATR). This section of the chapter discusses different methods.

The trajectory of the intercontinental ballistic missile's midcourse is essentially dual-body motion.

The fundamental equation for dual-body motion is:

$$r'' + \frac{\mu}{|r|^3} r = 0 \quad (5)$$

Where geocentric distance vector represented as r^n with order two, the earth's gravitational constant denoted as μ .

3.1 Micromotion feature

Various types of targets have dissimilar friction features during trajectory operation. In the fretting characteristics of warheads, angular velocity is taken into account, as is swing in the fretting characteristics of heavy baits, and random frequency roll in the fretting features of light baits, boosters and also fragment groups. The warhead rotates in a vector direction while spinning around its own symmetry axis. Precession is the name given to this period of rotation. The angle of precession is the angle formed by the axis of symmetry and the vector's direction (**Figure 1**).

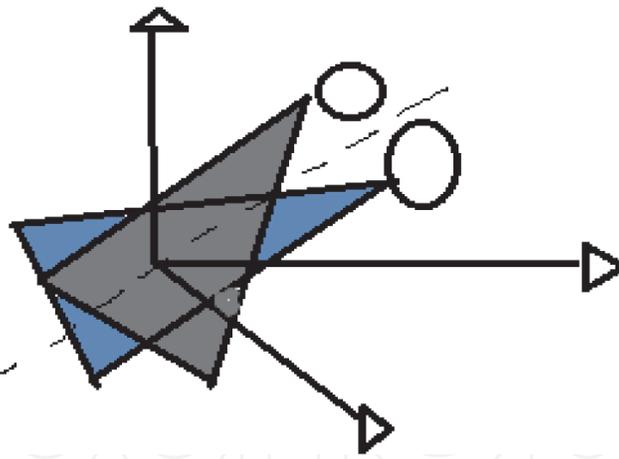


Figure 1.
Warhead precession model.

The orbit causes the bait to swing in a vertical plane, and the difference of the swing angle is $\theta = \theta(t) = \theta_s \sin \omega_s t$ Where θ_s is the swing amplitude and ω_s swing angle frequency.

The target acquisition with dynamic RCS sequence is influenced by attitude angle. Altitude is the angle between line of sight of the radar and target axis. Using the sequence of attitude angles, the target static RCS library, target dynamic RCS sequence can be obtained [14].

3.2 Trajectory information

The author of this paper described a technique for quickly identifying a warhead during boost phase by combining kinematic information obtained from the target's trajectory through an enhanced Kalman filter by means of a constant jerk model. During the boost phase, the main factors influence on the missile are engine thrust along with gravity, and air resistance, with engine thrust being the most potent. After separation, the warhead and the wreckage of the uncontrolled components have a significant difference. Although the warhead speeds, the wreckage does not. Because the missile is flying at a low angle of attack, the thrust acceleration is nearly parallel to the ground during the boost phase. As a result, during the boost phase the warhead acceleration on velocity is rather substantial. Once the wreckage has been separated, gravity and air resistance are the main forces act on it. However, as the rubble falls, it can be enjoyable after a while. As a result, the target's upward velocity component and the projection of acceleration on velocity are chosen as the recognition method's two properties. To obtain more precise target motion data, an extended Kalman filter with constant jerk model is utilized, which improves recognition performance by lowering the impact of radar measurement noise [6, 15].

3.3 Radar cross-section (RCS) time series, micro-Doppler information

Because warheads and ambiguous objects exhibit a variety of micro-motions throughout their ballistic trajectory, the micro-Doppler effect analysis, which was presented and has been extensively studied in recent years was utilized to generate reliable information for target detection. While precession and nutation define warhead flight, the intriguing objects just wobble due to the lack of a phase motor control. When analyzing the gathered radar data, these various micro-motions result in diverse micro-Doppler fingerprints. A unique feature extraction strategy based on Krawtchouk (Kr) moments is proposed in this research for ballistic target categorization. Because of their unique properties, Kr-moments are commonly

employed in image processing applications such as image reconstruction, shape and face recognition. Since Kr moments do not require numerical approximation because they are discretely defined, as opposed to continuous orthogonal moments. Because of the reiteration relations and symmetry qualities of Krawtchouk moments, there is no discretization error and therefore resource essential to store the polynomials is minimized. Kr-moments are used in this work for analyzing micro-doppler signature [7].

3.4 High-resolution range profile (HRRP)

To improve the range and angular resolution of tracking, high-resolution radars (HRRs) use broadband signals and synthetic apertures. They also provide, two or more -dimensional high-resolution scans carrying information about the intended characteristic of the target, which can be used to exactly classify and identify the targets. Range-Doppler imaging, phase-derived ranging, and micro-motion characteristics are all obtained using advanced signal processing methods in HRRs. However, issues such as reduced SNR and tracking precision of multi-scatter point targets limit the benefits and applications of HRRs. The author explains the novel HRR technologies and addresses the difficulties and keys related to detection, tracking, imaging in this study. Lastly, it examines the most recent developments and representative findings from HRR-based research [8]. The target signature's inverse Radon transform is characterized by a high-resolution range profile frame collected inside a full period of the target's key rotation, is computed in this study to provide a new approach for the categorization of ballistic targets. The precession of warheads and the tumbling of decoys are also considered. The classifier's final feature vector is determined by the pseudo-Zernike moments of the subsequent transformation. The extracted features ensure resilience contrary to the target's size and velocity of rotation, as well as the target's beginning motion phase [5, 16, 17].

3.5 Images from synthetic aperture radar (SAR)

For synthetic aperture radar (SAR) target detection, a multi-criteria sparse depiction-based classification (SRC) is devised. To generate the coefficient vector throughout the global dictionary sparse representation is applied. As a result, categorization is based on three alternative choice criteria: minimum global and local reconstruction reconstruction errors, and maximum coefficient energy. Each of the three rules approaches the coefficient vector in a unique way, allowing them to complement one another. After performing a linear combination on the three outcomes using an adaptive weighting approach, a final judgment is made [18–21].

4. Deep learning technique for radar target identification

Decoys, debris, and trash are frequently convoy near the real warhead during the midcourse of a ballistic missile to boost the missile's penetrating capacity. This interferes with the identification of the real warhead via radar. Since absence of atmospheric drag, the fake targets approach the warhead at a high rate, producing a target assembly. Their macro motions remain same, but their micro motions differ, resulting in RCS time sequence differences. This is the foundation to distinguish between real and false targets.

Deep neural networks (DNNs) have recently been a prevalent study topic in classification. DNNs can learn high-level depictions from large datasets, proceeding with the state of the art in a range of challenging problems and fields. In image

classification, language understanding, speech recognition, and a number of other domains. This will enable DNNs to be used successfully in a wider range of fields. Deep recurrent neural networks, deep feed-forward neural networks, and convolutional neural networks are some of the several types of DNNs.

4.1 Recurrent neural network

The capacity of RNNs to function with conceptual classifications is well-known. The RNN can recall previous time step outputs and use them to make judgments for the current step. The RNNs' chain structure suggests that they can be used intuitively with sequences. The current time-step input in an RNN is made up of new data and the total network's output from the previous time-step. As demonstrated in **Figure 2**, any gradient-based optimization strategy used to train an RNN may encounter the vanishing gradient issue at some time [9]. Furthermore, if data from multiple time steps or more is required before making a decision by the current time step, it may be unable to provide a precise prediction. 'Long ShortTerm Memory' (LSTM) is a technique that helps to solve this issue [10, 11]. The vanishing gradient problem is addressed in the LSTM by incorporating three gated units: a forget, input and output, and a forget gate respectively [9–11, 22, 23].

Conventional RNN is shown in **Figure 2**, the RNN is defined as

$$h_k = \varphi_h(w^{hi}i_k + w^{hh}h_{k-1}) \quad (6)$$

$$o_k = \varphi_o(w^{oh}h_k) \quad (7)$$

4.2 Convolution neural network

Like a standard multilayer neural network, a Convolutional Neural Network (CNN) is made up of multiple convolutional layers followed by multiple fully linked layers. The CNN architecture is intended to take use of the 2D structure of a picture. To provide translation invariant features, resident connections and weights are used, followed by some sort of pooling. With the lesser parameters than fully linked networks with the similar number of hidden units makes CNNs easier to train. A $m \times m \times r$ picture is used as the input to a convolutional layer, where m is the image's height and breadth and number of channels is denoted by r . The k filters of size $o \times o \times q$ constitute the convolutional layer, where 'o' is less than the image's dimension and q may be similar as or less than the number of channels r , and even may vary for each kernel. Filters size creates connected structures are then

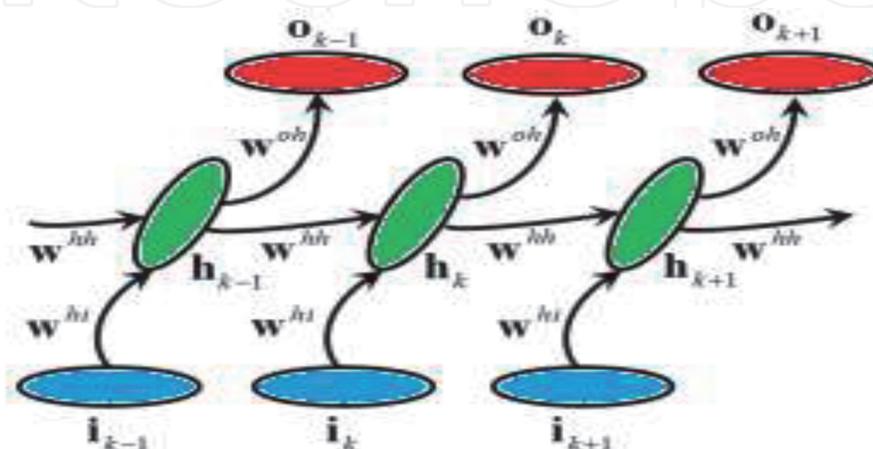


Figure 2.
 Recurrent neural network consists of input, hidden and output layer.

convolved with the picture to create k feature maps of size $m-o + 1$. Each map is then subsampled using mean or maximum pooling over $p \times p$ connecting regions, with p ranging from 2 for small images to 5 for bigger images.

Before or after the subsampling layer, each feature map is given additive bias and sigmoidal nonlinearity. **Figure 3** shows a typical convolutional neural network architecture, which includes two convolutional layers, two maximum pooling layers, and one fully connected layer.

CNN structure with one dimensionality was designed for warhead and decoy classification based on RCS time series based on ten missile paths are simulated, each with the same shape warhead and decoy but varied micro-motion [24]. RCSnet, a 1D convolutional neural network structure that employs the radar cross-section (RCS) time series to identify warhead and decoy targets of the same form in mid-flight, was presented. On a simulation dataset, it was compared to 5 typical classification methods that utilized 26 selected features [19, 25].

The SCF signature pattern classification approach uses a noise-resilient and unique 2-D signature pattern formed by the spectral correlation function (SCF) and a robust deep belief network (DBN) deep learning algorithm. The radar system was set up in a lab setting, information was acquired for three micro UASs, and the data was used to test the signal processing technique [26]. For detection of sea-surface targets, a faster region-based convolutional neural network (Faster R-CNN) was developed. It uses a deep convolutional network to extract visual features and detects them using the “selective search + CNN + SVM” method. R-CNN training takes a long time and takes up a lot of disc space [21, 23, 27].

4.3 Support vector machine

SVM works by determining the best classification hyperplane that meets the classification criteria and optimizes the margin areas on both sides of the hyperplane while preserving classification precision. SVM algorithms include linear branched support vector machines, linear support vector machines, and non-linear support vector machines. If the input space has non-linear separability, an appropriate non-linear mapping is used to move the sample points from the input space to

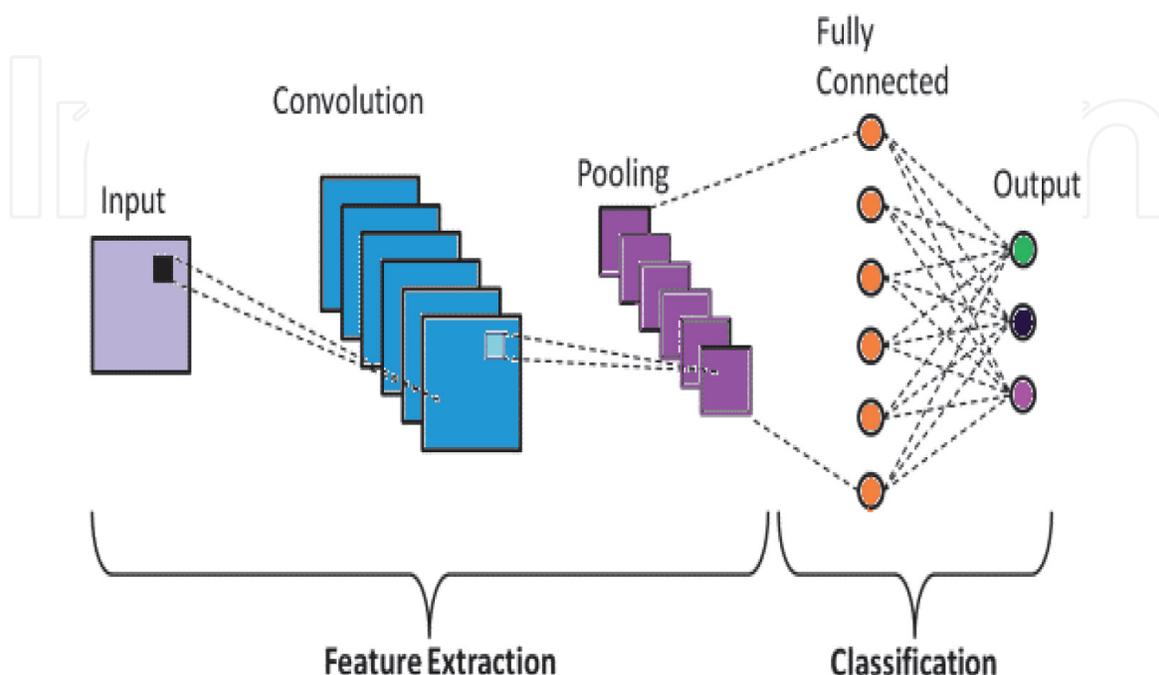


Figure 3.
Architecture of convolutional neural network.

References	Method	Findings
[22]	RNN: Using Physical optics RCS data for all possible aspect angle and elevation are estimated	Open-source tool called POFACETS used for creating RCS database as a function of aspect angles. This technique provides 95% accuracy using the data based created. But not suitable for the noisy condition.
[28]	Target dynamics are modeled, target is treated as appoint object	Sates estimation accuracy is not sensitive to the maneuvers and quantitative analysis is difficult due to the involvement of convex optimization
[24]	MSTAR data set consisting of 10 military target SAR images	Feature extraction by constructing a multistage network to learn SAR images. High computational complexity and delay is processing is observed.
[25]	CNN	Training time using RCSnet is longer than conventional method. Not suitable for real time application.
[29]	SVM	Statistical feature extracted from RCS time series. This method is more sensitive to the number of samples and unstable for larger data set

Table 1.
References with method and findings were summarized.

a high-dimensional feature space, resulting in linear separability in the feature space for the corresponding sample points.

The motion trajectory and micromotion features of seven different types of targets are combined to mimic dynamic RCS sequences of diverse targets. The above data is then used to extract 10 statistical features with separation qualities, such as position feature, distribution feature, and transform domain feature parameters. In a complicated scenario, the SVM method is used to classify and detect multitargets (**Table 1**) [29].

5. Summary

The main aim of this work is to find the warhead and decoy classification and identification. Classification of radar target is one of the utmost imperative and hardest practical problems in finding out the missile. Detection of target in the pool of decoys and debris is one of the major radar technology widely used in practice. In this study we mainly focus on the radar target recognition in different shapes like cone, cylinder and sphere based on radar cross section (RCS). RCS is a critical element of the radar signature that is used in this work to identify the target. The concept is to focus on new technique of ML for analyzing the input data and to attain a better accuracy. Machine learning has had a significant impact on the entire industry as a result of its high computational competency for target prediction with precise data analysis. Among the Various ML techniques, convolutional neural networks perform better than support vector machine.

Conflict of interest

The authors declare no conflict of interest.

IntechOpen

Author details

Rashmi Narasimhamurthy^{1*} and Osamah Ibrahim Khalaf²

1 Department of Electronics and Communication Engineering, BMS Institute of Technology and Management, Bangalore, India

2 Al-Nahrain University, Baghdad, Iraq

*Address all correspondence to: rashmiswamy@bmsit.in

IntechOpen

© 2021 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/3.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

- [1] Fetter, S., Sessler, A. M., Cornwall, J. M., Dietz, B., Frankel, S., Garwin, R. L., ... & Wright, D. C. (2000). Countermeasures: a technical evaluation of the operational effectiveness of the planned US national missile defense system.
- [2] Gao, H., Xie, L., Wen, S., & Kuang, Y. (2010). Micro-Doppler signature extraction from ballistic target with micro-motions. *IEEE Transactions on Aerospace and Electronic Systems*, 46 (4), 1969-1982.
- [3] Lei, P., & Liu, Y. X. (2012, October). Feature extraction and target recognition of missile targets based on micro-motion. In *2012 IEEE 11th International Conference on Signal Processing (Vol. 3, pp. 1914-1919)*. IEEE.
- [4] Persico, A. R., Ilioudis, C. V., Clemente, C., Soraghan, J. J. "Novel classification algorithm for ballistic target based on HRRP frame", 'Institute of Electrical and Electronics Engineers (IEEE)', 2019
- [5] Teng Long, Zhennan Liang, Quanhua Liu. "Advanced technology of high-resolution radar: target detection, tracking, imaging, and recognition", *Science China Information Sciences*, 2019
- [6] Chen, J., Xu, S., Tian, B., Wu, J., & Chen, Z. (2015). A fast recognition method of warhead target in boost phase using kinematic features. *MIPPR 2015: Automatic Target Recognition and Navigation*. doi:10.1117/12.2207401.
- [7] Persico, A. R., Clemente, C., Pallotta, L., De Maio, A., & Soraghan, J. (2016). Micro-Doppler classification of ballistic threats using Krawtchouk moments. *2016 IEEE Radar Conference (RadarConf)*. doi:10.1109/radar.2016.7485086
- [8] Long, T., Liang, Z. & Liu, Q. Advanced technology of high-resolution radar: target detection, tracking, imaging, and recognition. *Sci. China Inf. Sci.* 62, 40301 (2019).
- [9] Gao, C., Liu, H., Zhou, S., Su, H., Chen, B., Yan, J., & Yin, K. (2018, August). Maneuvering target tracking with recurrent neural networks for radar application. In *2018 International Conference on Radar (RADAR)* (pp. 1-5). IEEE.
- [10] Bhattacharyya, Kaustubh & Sarma, Kandarpa. (2012). Automatic Target Recognition (ATR) System using Recurrent Neural Network (RNN) for Pulse Radar. *International Journal of Computer Applications*. 50. 10.5120/7960-1154.
- [11] Wang, L., Tang, J., & Liao, Q. (2019). A Study on Radar Target Detection Based on Deep Neural Networks. *IEEE Sensors Letters*, 1-1. doi:10.1109/lens.2019.2896072
- [12] www.armscontrol.org
- [13] Persico, A. R., Clemente, C., Gaglione, D., Ilioudis, C. V., Cao, J., Pallotta, L., ... & Soraghan, J. J. (2017). On model, algorithms, and experiment for micro-Doppler-based recognition of ballistic targets. *IEEE Transactions on Aerospace and Electronic Systems*, 53 (3), 1088-1108.
- [14] Wenbo Tang, Lei Yu, Yinsheng Wei, Peng Tong. "Radar Target Recognition of Ballistic Missile in Complex Scene", *2019 IEEE International Conference on Signal, Information and Data Processing (ICSIDP)*, 2019.
- [15] Chen, Jian, Shiyu Xu, Biao Tian, Jianhua Wu, and Zengping Chen. "A fast recognition method of warhead target in boost phase using kinematic features",

MIPPR 2015 Automatic Target Recognition and Navigation, 2015

[16] A. R. Persico, C. V. Ilioudis, C. Clemente and J. J. Soraghan, "Novel Classification Algorithm for Ballistic Target Based on HRRP Frame," in *IEEE Transactions on Aerospace and Electronic Systems*, vol. 55, no. 6, pp. 3168-3189, Dec. 2019, doi: 10.1109/TAES.2019.2905281.

[17] Bharat Sehgal, Hanumant Singh Shekhawat, Sumit Kumar Jana. "Automatic Target Recognition Using Recurrent Neural Networks", 2019 International Conference on Range Technology (ICORT), 2019

[18] Junhua Wang & Yongping Zhai (2021) Target recognition of synthetic aperture radar images using multi-criteria SRC, *Remote Sensing Letters*, 12: 8, 739-749, DOI: 10.1080/2150704X.2021.1934594

[19] Ali El Housseini, Abdelmalek Toumi, Ali Khenchaf. "Deep Learning for target recognition from SAR images", 2017 Seminar on Detection Systems Architectures and Technologies (DAT), 2017

[20] Junhua Wang, Yongping Zhai. "Target recognition of synthetic aperture radar images using multi-criteria SRC", *Remote Sensing Letters*, 2021

[21] weaponsandwarfare.com

[22] Sehgal, B., Shekhawat, H. S., & Jana, S. K. (2019). Automatic Target Recognition Using Recurrent Neural Networks. 2019 International Conference on Range Technology (ICORT). doi:10.1109/icort46471.2019.9069656

[23] Li Wang, Jun Tang, Qingmin Liao. "A Study on Radar Target Detection Based on Deep Neural Networks", *IEEE Sensors Letters*, 2019.

[24] Jiang, W., Ren, Y., Liu, Y. et al. A method of radar target detection based on convolutional neural network. *Neural Comput & Applic* 33, 9835–9847 (2021). <https://doi.org/10.1007/s00521-021-05753-w>

[25] Carrera, E. V., Lara, F., Ortiz, M., Tinoco, A., & Leon, R. (2020). Target Detection using Radar Processors based on Machine Learning. 2020 IEEE ANDESCON. doi:10.1109/andescon50619.2020.9272173

[26] Chen, Jian & Shiyou, Xu & Chen, Zengping. (2018). Convolutional neural network for classifying space target of the same shape by using RCS time series. *IET Radar, Sonar & Navigation*. 12. 10.1049/iet-rsn.2018.5237.

[27] Yan, H., Chen, C., Jin, G., Zhang, J., Wang, X., & Zhu, D. (2021). Implementation of a Modified Faster R-CNN for Target Detection Technology of Coastal Defense Radar. *Remote Sensing*, 13(9), 1703.

[28] T. Tang, C. Wang and M. Gao, "Radar Target Recognition Based on Micro-Doppler Signatures Using Recurrent Neural Network," 2021 IEEE 4th International Conference on Electronics Technology (ICET), 2021, pp. 189-194, doi: 10.1109/ICET51757.2021.9450934.

[29] W. Tang, L. Yu, Y. Wei and P. Tong, "Radar Target Recognition of Ballistic Missile in Complex Scene," 2019 IEEE International Conference on Signal, Information and Data Processing (ICSIDP), 2019, pp. 1-6, doi: 10.1109/ICSIDP47821.2019.9172943.