

# Classification of Ground Moving Radar Targets with RBF Neural Networks

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Abstract: This paper presents a novel method for classification of targets detected by Ground Moving Target Indication (GMTI) radar systems. GMTI radar systems provide no direct information regarding the type or size of the detected targets. The suggested method allow classification of ground moving targets into few groups of size, by analysis of Signal to Noise Ratio (SNR) values of GMTI radar measurements. The classification method is based on Radial Basis Function (RBF) neural networks. The data used as features for classification composed of Radar Cross Section (RCS) values of the target (obtained from the SNR values) in varying aspect angles. The proposed classifier was tested on diverse simulative cases and yielded very good results in classification of targets for three groups of size.

## 1 INTRODUCTION

Target classification for a GMTI radar system is a challenging task due to the lack of any information regarding the target's spatial size or shape in the radar's raw data (Blackman and Popoli, 1991)–(Skolnik, 1962). On the other hand, such a feature is vital due to the growing need to provide indication regarding the type of detected radar targets when no optical sensors are available. Therefore, for the past decades many researches turned their effort to introduce a method for estimating the size of the targets from the radar raw data (Vespe, 2007)–(Zhao and Bao, 1996).

Vespe, in his Ph.D. thesis (Vespe, 2007), gives a survey of the methods developed for GMTI target classification. The author describes three fundamentals classification methodologies. The first methodology relay on a database of previously collected measurements to form a library of templates (a series of class-labeled patterns). Classification of a new target is based on comparison of the pattern formed by the target's measurements, and the patterns in database. However, it can be very difficult to obtain enough measurements to construct a reliable database. The second methodology relays on Computer Aided Design (CAD) target models, and computational prediction of targets' radar measurements or features. The possibility of modeling any target class having any

possible configuration is the principal advantage of this method, counterbalanced by the difficulty of obtaining reliable simulated measurements. The third method relays on a priori knowledge of the target's physical and electrical characteristics, offering the advantage of classification which does not require radar measurements to represent the target class.

The following paragraphs describe methods for radar target classification based on the RCS signature of targets (Register et al., 2008), (Backes and Smith, 2013), (Lee et al., 2016). RCS signature of a target is the RCS value measured in every given orientation of the target. The orientation of the target is determined by the aspect angle, i.e. the angle between the radar's Line of Sight (LOS) and the target's velocity direction. RCS values are not obtained directly from the radar measurements, but extracted from the SNR of radar measurements using the radar equation (Skolnik, 1962).

The work of A. Register et al. (Register et al., 2008), use RCS measurements as a feature for target classification. The authors aim to classify radar targets by associating the detected target to one of two types, a reentry vehicle (RV) and a tank. The classification is performed by a decentralized fusion algorithm which is provided with results from Local Decision Functions (LDFs). The LDFs provide a decision regarding the targets identity, based on the RCS characteristics of the target. The RCS values are

extracted from SNR measurements, measured across multiple dwells. The classifier was tested on simulations of X-band radar observing an RV and a tank. In some cases, the LDFs showed unstable classification results. However, the fusion algorithm was found efficient and manage to replace false decisions of the LDFs.

T. Backes and L. D. Smith (Backes and Smith, 2013) attempt to improve RCS estimation by data censoring methods. The authors refer to two different methods for data censoring. In the first method, the data is censored through the removal of values that cross a certain maximum or minimum threshold. In the second method, the data is censored by removing a fixed quantity of peripheral samples. For target classification, the authors use a **Maximum Likelihood Estimator (MLE)** based on Swerling III and IV distribution models of mean RCS. The paper provides a comparison between the error biases of conventional, uncensored MLE and censored MLE using the first censoring method. The classification results show that censored MLE performance substantially exceeds the performance of the conventional MLE.

S. Lee et al. (Lee et al., 2016) present a method to design a fuzzy classifier to classify shell-shaped targets. The classification is based on RCS measurements with consideration of the aspect angle and polarization dependencies in various flight scenarios. The fuzzy classifier consists of membership functions (MFs) which relate the RCS value to the probability that the input belongs to each specific target class. The authors suggest three different MFs Gaussian, trapezoidal, and triangle MF. Particle Swarm Optimization (PSO) is applied to optimize MF parameters, to maximize classification capabilities. PSO is a stochastic search method, effective in optimizing difficult multidimensional problems. The classifier was tested in simulative environment. The best performance was given by Gaussian fuzzy, achieving 75% hit-rate.

The works mentioned above do not present a comprehensive general method for classifying ground moving radar targets. The reason is that SNR values are characterized by large variances, and thus samples of targets from different classes overlap each other. In addition, the reflected signal's SNR values are very sensitive to changes in aspect angle (the angle between the intrinsic wave direction and the target's orientation). Even a slight change in aspect angle can cause fluctuations of 20 dBsm, in SNR values (Skolnik, 1962).

This paper presents a new method for classifying the GMTI radar targets based on Radial Basis Functions (RBF) neural networks (Bishop et al., 1995) us-

ing RCS measurements with consideration of the aspect angle. RBF neural networks provide non-linear classification and robust performance in classification of data characterized by large variances, when the classification is only into several classes. Containing only one hidden layer, these networks offer the advantage of short training time, fast classification, and relatively simple implementation. Considering the characteristics of the raw data provided by GMTI radar measurements, and the low number of classes, this type of networks was found suitable for achieving our goal.

RBF networks for classifying targets have already been used in some previous works (Guosui et al., 1996)–(Zhao and Bao, 1996). L. Guosui et al. (Guosui et al., 1996), used modified RBF networks for classifying between moving targets of man, bicycle and truck. Unlike our work, the data used for classification was Doppler frequency spectrum of the radar measurements. In addition, the classifier presented in the current work is restricted to classification of motorized vehicles alone to classes that possess much less distinctive characteristics. Also, the work of Q. Zhao and Z. Bao (Zhao and Bao, 1996) was restricted to 3 different military aircrafts, and does not introduce the ability to classify ground moving targets.

This paper is organized as follows. Section 2 provides a general introduction to Neural Networks and the RBF network. Section 3 presents the implementation of RBF network for GMTI radar target classification. Section 4 describes the simulations and result. Finally, in Section 5 we present the conclusions of this work.

## 2 NEURAL NETWORKS AND RBF NETWORK

This section is composed of two subsections. The first subsection provides a general background on the topic of artificial networks. The second subsection concentrates on RBF neural networks.

### 2.1 Neural Networks

Artificial neural networks are mathematical models for data processing which are inspired by the structure of the mammal brain (Bishop et al., 1995). A large artificial neural network might have hundreds or thousands of processing units, while there are simpler networks composing of tens of processing units. The processing units are denoted as neurons. The neurons are organized in layers. The first and last layers are referred to as input and output layers, and in between



there are one or more additional layers, which are referred to as hidden layers.

The use of neural networks involves feature extraction. This means that we do not use all the data regarding our classification problem, not in the training stage, nor in the activation of the network. To reduce complexity, processing time, and enhance performance, one must choose only certain features of the subject for classification, which represent the subject/class in the best way, and will be the input of the network.

Neural Networks (NN) based algorithms are used to solve a variety of problems, such as speech recognition, data mining, medical diagnosis, and computer vision. Most importantly for the case of this paper, NN based algorithms have been found very useful for complex, nonlinear classification tasks. For the scope of this work, supervised learning is especially relevant, where the class of each target in the training database is known, and used in the procedure of network training.

## 2.2 RBF Networks

A Radial Basis Function, is a real valued function in which the value is determined by the distance between the input vector and the origin or a given center, i.e.

$$\phi(x, c) = (\|x - c\|) \quad (1)$$

where  $x$  is an input vector of dimension  $d$  and  $c$  is the center vector of the same dimension. We can use the RBF to approximate any given function  $y(x)$  as a weighted sum over  $M$  basis functions.

$$\mathbf{y} = \sum_{i=1}^M \omega_i \phi(\|x - c_i\|) \quad (2)$$

where  $w_i$  is the  $i^{th}$  weighting coefficient and  $c_i$  is the appropriate center. It can be shown that any continuous function on a given interval can be interpolated with arbitrary accuracy by this summation, for sufficiently large number of  $M$  (Bishop et al., 1995).

The scalar equation 2, can be generalized to a multivariate equation of any dimension  $K$ , where each component is given by such weighted sum.

$$\mathbf{y}(k) = \sum_{i=1}^M \omega_{ik} \phi(\|x - c_i\|), \quad k \in [1, \dots, K] \quad (3)$$

Equation 3 can be represented as a neural network as demonstrated in Fig.1. The RBF network is constructed from three basic layers: input, hidden, and output. In Fig.1 the input is the vector  $x$ , the hidden layer is constructed from the  $M$  functions  $\phi(x)$ , and the output is constructed from  $K$  classes.

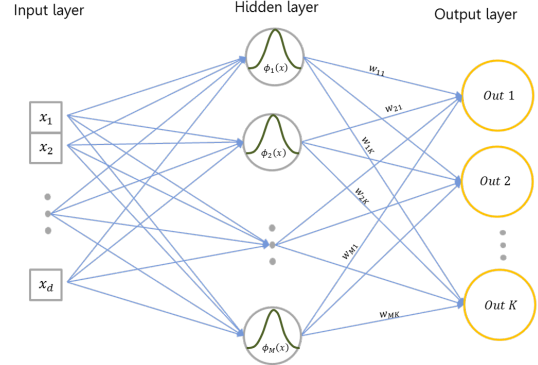


Figure 1: RBF network architecture:  $x = [x_1, \dots, x_d]$  is the input vector- layer no. 1,  $\phi_1, \dots, \phi_M$  are the activation functions-layer no. 2,  $W_{11}, \dots, W_{MK}$  are the weights, and layer no. 3 is constructed of  $k$  output classes.

During classification procedure, the feature vector is sent to each of the activation functions as an input. Each of the activation functions provides a value corresponding to the features of the target,  $\phi_i(x)$ . The output of the hidden layer is an  $M$  dimensional activations vector.

$$\Phi(x) = [\phi_1(x), \dots, \phi_M(x)], \quad \Phi \in \mathbb{R}^M \quad (4)$$

The final output of the RBF neural network is a  $K$  dimensional vector  $\mathbf{y}$ , obtained by a multiplication of the activations vector by an optimized weights matrix  $W$  (the optimized weights matrix is constructed during the training procedure).

$$\mathbf{y} = W \cdot \Phi(x), \quad W \in \mathbb{R}^{K \times M} \quad (5)$$

The component  $k$  of the vector  $\mathbf{y}$

$$\mathbf{y}(k) = \sum_{i=1}^M [W]_{k,i} \phi_i(x) \quad (6)$$

is assigned to class  $k$  in the output layer. The value of each component of the vector  $\mathbf{y}$  represents the assignment score to the appropriate class. The class with the highest compatibility score is the predicted class.

$$\text{ClassPrediction} = \underset{k \in [1, 2, \dots, K]}{\operatorname{argmax}} \{ \mathbf{y}(k) \} \quad (7)$$

In advance of the classification procedure described above, the network is trained using a database containing measurements of known targets. In the first step the measurements are divided into  $M$  clusters by an unsupervised clustering algorithm. Then, the weights between the hidden layer, and output layer, (the components of the  $W$  matrix) are calculated by a supervised training algorithm (Bishop et al., 1995).

### 3 THE PROPOSED METHOD FOR TARGET CLASSIFICATION USING RBF NETWORKS

This section provides a description of the features extraction procedure, and the implementation of the RBF network, for GMTI radar targets classification.

The features we use are RCS values of the targets at various aspect angles. In our simulations, the targets are assumed to be symmetrical with respect to axes  $x$  and  $y$ . Therefore, every aspect angle can be projected into the range of  $[0 - 90]$ . The aspect angles are divided into 9 domains:  $[0, 10) \subseteq \alpha_1, [10, 20) \subseteq \alpha_2, [20, 30) \subseteq \alpha_3$ , etc.

When a target is detected, the radar system uses a tracker to associate consecutive radar observations (known as "plots") of the target into a track. Using tracking information the direction of the target's velocity is obtained, and the aspect angle of the target in each plot is calculated.

The RCS of the target is extracted from the SNR value of each plot using the Radar equation (Skolnik, 1962). Each RCS value is assigned to the appropriate element of the feature vector according to the aspect angle of the target in the corresponding plot. When few plots fall in the same angle domain, the average RCS value of these plots is used. We note that the choice of number of plots for classification introduces a trade-off between accuracy and duration of the classification procedure: the more plots used for classification; the more time is invested for collecting them.

In most cases, the target is not observed at all angle domains, i.e. some of the elements in the feature vector do not contain information. In these cases, the value '0' is assigned to the regions with no available information. The value '0' means no information regarding the target, rather than actual '0' value. Therefore a weights vector is concatenated to the feature vector, to 'mark' the elements with no information. The weights vector consists of the value '100' in elements which correspond to regions that contain information, and the value '0' in all other cells. This enables the network to adapt to those cases in which the feature vector is partial, and enhances the versatility of the classifier.

For a given target, the feature vector corresponds to a unique pattern of RCS values with respect to aspect angles. Using a substantial amount of these vectors as a training set, we can train the network to recognize the typical pattern of each class, and in turn, use it for classification when new unknown measurements are acquired.

In the current work, the activation functions  $\{\phi_i\}_{i=1}^M$  of the hidden layer are Gaussian functions

with expectancy  $\mu_i$  and the covariance matrix  $\Sigma_i$ .

$$\phi(x) = e^{-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i)} \quad (8)$$

The parameters of the activation functions and the weights matrix are determined during training procedure using a database of  $N$  observations  $\{x_i\}_{i=1}^N$  of known targets  $\{t_i\}_{i=1}^N$ . Each target is labeled according to its class. For example, a target of class  $k \in \{1, \dots, K\}$  is labeled by the vector  $t_i = [t_{i1}, \dots, t_{iK}]^T \in \mathbb{R}^K$ , where  $t_{ij} = \begin{cases} 1, & j = k \\ 0, & \text{else} \end{cases}$ .

In the first stage of training, the training data points are divided to  $M$  subsets by the k-means clustering algorithm. The expectancies  $\{\mu_i\}_{i=1}^M$  of the activation functions are determined by the mean vectors of the data points of in each subset. The covariance matrices  $\{\Sigma_i\}_{i=1}^M$  are determined according to the average square distance between the observations of each subset and the mean vector of each subset.

In the second stage of training the values of the weights, i.e. the elements of the weights' matrix  $W$ , are given by the solution of the following least squares problem:

$$\begin{aligned} & \text{Minimize}_{W \in \mathbb{R}^{K \times M}} \{(W \cdot \Psi - T)^T (W \cdot \Psi - T)\} \\ & \Phi(x) = [\phi_1(x), \dots, \phi_M(x)] \quad , \quad \Phi \in \mathbb{R}^M \\ & \Psi = [\Phi(x_1), \dots, \Phi(x_N)] \quad , \quad \Psi \in \mathbb{R}^{M \times N} \\ & T = [t_1, \dots, t_k] \quad , \quad T \in \mathbb{R}^{K \times M} \end{aligned} \quad (9)$$

Where  $\Phi$  is the activation vector,  $\Psi$  is the activation matrix and  $T$  is the target matrix. The solution of the least squares problem is given by

$$W^T = \Psi^\dagger \cdot T \quad (10)$$

### 4 SIMULATION & RESULTS

In this section, we introduce the simulated database, and a performance analysis of the suggested classifier.

The database of radar plots is based on 14 target models which were designed per dimensions of known vehicles (e.g. Mazda 3, Mercedes truck, Ford pick-up truck, etc.). The observations are obtained in many different GMTI simulated scenarios. We simulate a database which consists of 30,000 radar detections. To test the classifier, the database is divided into two parts: 70% of the data is used as training data, and 30% is used as test data. The aspect angle and the RCS value of each observation are calculated as explained in section 3. In addition, since we are working with simulated data, the ID number which defines the identity of the detected target is known.

Fig.2 present a comparison between classifications as function of the numbers of radar plots. The results refer to classification of targets to three and five classes of size.

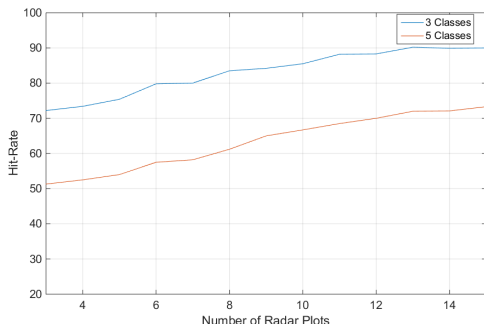


Figure 2: Classification hit rates for 3 and 5 classes as function of the number of radar plots used for classification.

As Fig.2 demonstrates, classification hit rates for cases of few radar plots are low. As we take more radar plots in consideration, the data obtained regarding the target is more robust and allows for higher accuracy in classification. The downside of classification using many radar plots is the time consumed for acquiring these plots. We found that using 10 radar plots enables classification with good performance for 3 classes, while increasing the number of plots does not substantially enhances performance. In addition, Fig.2 shows that classification into five classes of size results with an inferior performance compared with classification into three classes of size, because it needs to differentiate between more target types, and hence it has more mis-classifications.

In Fig.3, we present the Receiver Operating Characteristic (ROC) curves that show true positive classification rates versus true negative classifications rates. Classification of middle-sized targets to the middle-size class is considered a true positive classification. Classification of other targets to the middle-size class is considered a true negative. The curves relate to distinctions of targets to three or five classes. Choosing between three- or five-classes distinctions introduces the trade-off between achieving a more delicate distinction and achieving results with higher reliability.

In Table 1 and Table 2, the results are presented by confusion matrices to demonstrate the classifiers performances. The rows of each matrix represent the actual class of the target, while the columns represent the predicted class. In table the classes are arranged by increasing size of vehicles. The first class (A) represents the smallest vehicles, and the last class represents the largest vehicles. From table 1 we can extract that, for example, out of 152 true small vehicles, we were correct in 123 vehicles and the other vehicles

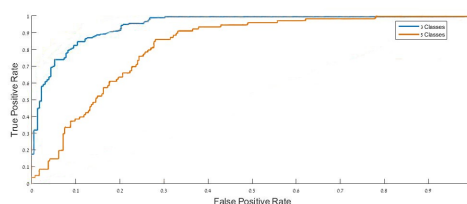


Figure 3: ROC curves for distinction between three or five classes. True positive means - classification of middle-size targets to the middle-size class and classification of other targets to the middle-size class is considered as true negative.

Table 1: Confusion Matrix for Three Classes Distinction.

		Predicted class		
		A	B	C
Actual class	A	123	29	0
	B	12	159	5
	C	0	9	71

were predicted as medium size. No vehicle was predicted as a large one.

In general, the confusion matrices provide indication of the classifier's stability. The elements on the matrix's diagonal, which indicate correct classification, have much greater values than the rest. Elements which are located far from the matrix diagonal contain small or zero values, indicating that most targets which are miss-classified are usually classified to a neighbor class. These results show that the RBF classifier rarely makes 'big' mistakes such as classifying a small target as a big target. The confusion matrices also demonstrate the difficulty of classifying targets to high number of classes. By looking at Table 2, we can learn that distinction between class C, and class D is challenging.

Fig.4 presents a comparison of the performance of our classifier, with the results obtained by a Minimum Mean Square Error (MMSE) criterion based classification method. To perform classification based on the MMSE criterion, we use the training dataset to create an RCS-to-angle typical pattern for each class. The pattern is created by averaging the RCS values taken in every specific angle separately. Then for a given unknown target, the mean square error between the

Table 2: Confusion Matrix for Five Classes Distinction.

		Predicted class				
		A	B	C	D	E
Actual class	A	48	5	2	1	0
	B	9	50	17	4	0
	C	3	7	48	20	2
	D	0	3	34	39	4
	E	0	1	2	3	74

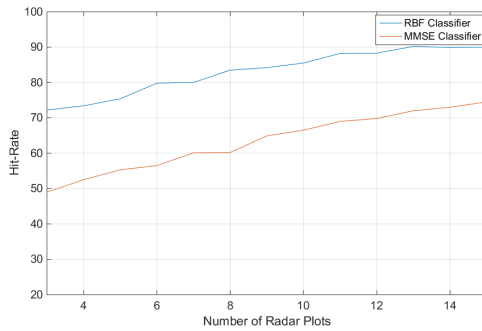


Figure 4: Comparison of the RBF network based classifier, and an MMSE based classifier performances. Hit Rate as Function of Measurements Number for classification to 3 Classes.

feature vector and the RCS-to-angle patterns of each class is computed. The target is assigned to the class with the minimum mean square error.

## 5 CONCLUSION

In this paper, a classifier for GMTI radar targets using RBF neural networks is proposed. The classification is done based on a feature vector which contains the RCS values in different observed aspect angle regions of the target. The proposed solution can also handle cases of insufficient data and classify target when the feature vector is not fully obtained. The above attribute makes the classifier suitable for real-time applications and offers added versatility. Comparison results have shown that our method is considerably better than the MMSE classifier for the same database. In addition, simulations have shown that this approach is suitable for classifying ground moving radar targets into 3 classes of size, with up to 90% hit-rate.

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## REFERENCES

Backes, T. and Smith, L. D. (2013). Improved rcs model for censored swerling iii and iv target models. In *Aerospace Conference, 2013 IEEE*, pages 1–4. IEEE.

Bishop, C., Bishop, C. M., et al. (1995). *Neural Networks for Pattern Recognition*. Oxford University Press.

Blackman, S. and Popoli, R. (1991). Design and analysis of modern tracking systems (artech house radar library. Artech house.

Guosui, L., Yunhong, W., Chunling, Y., and Dequan, Z. (1996). Radar target classification based on radial basis function and modified radial basis function networks. In *Proceedings of CIE International Conference of Radar, 1996.*, pages 208–211. IEEE.

Lee, S.-J., Jeong, S.-J., Kang, B.-S., Kim, H., Chon, S.-M., Na, H.-G., and Kim, K.-T. (2016). Classification of shell-shaped targets using rcs and fuzzy classifier. *IEEE Transactions on Antennas and Propagation*, 64(4):1434–1443.

Register, A., Blair, W., Ehrman, L., and Willett, P. K. (2008). Using measured rcs in a serial, decentralized fusion approach to radar-target classification. In *Aerospace Conference, 2008 IEEE*, pages 1–8.

Skolnik, M. I. (1962). *Introduction to Radar Systems*. McGraw-Hill.

Vespe, M. (2007). *Multi-Perspective Radar Target Classification*. PhD thesis, University of London.

Zhao, Q. and Bao, Z. (1996). Radar target recognition using a radial basis function neural network. *Neural Networks*, 9(4):709–720.