Distinction of Target and Chaff Signals by Suggesting the Optimal Waveform in Cognitive Radar using Artificial Neural Network

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ABSTRACT:
Using chaff to deflect missile guidance radar or missile seeker is a common and effective defense method in military vessels. To deal with this defensive method, focus on specific characteristics of the target and chaff signals. These features should be able to perform properly in different operating conditions of the radar or different environmental conditions that change the behavior of the radar's return signals. But there is no feature that can distinguish the target from the target with appropriate accuracy in all conditions. In this article, a structure is presented for detecting chaff and target in a radar and has been able to improve the accuracy of target detection in presence of chaff. Also, to improve the performance of the radar with a cognitive approach, its transmitted waveform is optimally selected and changed at each stage. For this purpose, a feedback neural network with LSTM layers has been used. The general structure of the proposed method uses pre-processing on the received radar signals and extracts symmetry characteristics, Doppler spread and AGCD from it to contain the information for separating the target and chaff. Then, to remove the effect of noise on the features. Finally, these features are used to correctly distinguish the target from the chaff in a feed-forward neural network with fully connected layers. At the end, the effectiveness of this method is compared to the previous methods. It can be seen that the performance of the proposed system has made a significant improvement in accuracy of detection.

KEYWORDS: Chaff, Target, Radar, Waveform, Artificial Neural Network

1. INTRODUCTION

Radar guidance system is used in anti-ship missiles in order to accurately guide missile to target and hit it with highest probability possible. Due to the need to lock on the target after searching and detecting the target, the radars are of tracking type. The most common and efficient methods against these types of radars is to create a fake passive target such as a radar decoy or throwing chaff. Considering that the missile guidance radar seeks the largest return in its range of vision, if it does not have the power to distinguish between the real and fake target, it will deviate towards the fake target whose radar cross-section is larger than the real target. This process is shown in the figure below.

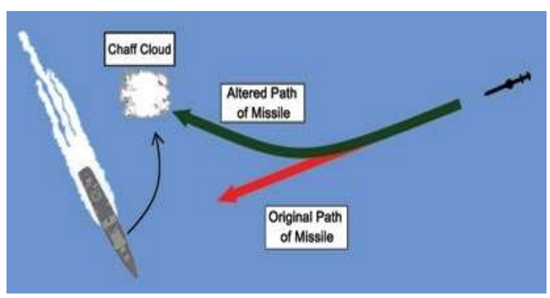

Fig. 1. How Chaff works in ship protection

It can be seen that the lock on the main target is broken and the missile is inclined towards the false target. To deal with this process, it is necessary for the radar to have the ability for distinguishing between the real and false targets. The figure below shows a view of

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how to shoot a chaff on a ship.

Fig. 2. The moment of throwing chaff.

Therefore, it is very important for the missile guidance radar to distinguish between the target and the chaff. For this purpose, two processes can take place. The first process is to analyze the information received by the radar to distinguish between the target and the chaff. If the missile guidance radar has the ability to correctly distinguish between the target and chaff, it has practically disabled the target's defense system. For this purpose, various articles such as [1-8] have presented suitable features that can be extracted from the received radar data to distinguish between target and chaff. The second process that can be done is to change the radar's working parameters during the target hunting process so that the distinction between the chaff and the target is maximized as much as possible. The working performance of the desired radar should be such that, in addition to having a different effect on the target and chaff, it should be easily changed during operation. According to these criteria, the waveform has been used in this research. Since the process of detecting the appropriate waveform depends on the received data and the environmental conditions, a deep neural network has been used for this purpose. In the previous article [9], the method of detecting the moment of Chaff firing was investigated. In this research, after determining the moment of firing, it is tried to distinguish the target from the chaff in each scan, and then it suggests the appropriate waveform to send at each subsequent moment. The general procedure is that, first, the received radar data is pre-processed and Doppler, symmetry and AGCD features are extracted. Previous researches [1-8] have shown that these features are suitable for distinguishing between the target and chaff. Finally, a deep neural network with LSTM layers was used to determine whether the used waveform had a suitable capability for data separation. The network has the duty to suggest the appropriate waveform at any moment according to the trend of waveform and environmental changes. The optimal waveform is the one that creates the most distinction between the target and chaff.

2. LITERATURE REVIEW

The activities of the researchers in this matter are divided into three areas: chaff characteristics, how to separate the chaff from the target, and how to optimize the radar detector. In the area related to chaff characteristics, in [1] Sherman et al., to analyze the bistatic RCS behavior of the chaff, presented models in which they model the chaff behavior in different polarizations and directions in coherent and incoherent ways.

NATO Research Center in [10] and Bell in [11] have provided a suitable analysis in the field of radar detector. In these articles, the efficiency of radar recognition in the fields of resource management, matched illumination and statistical control is discussed.

In [12], Wang et al. have used the information in the Range-Doppler plane to separate the chaff from the target. In this way, first the radar data is converted to the Range-Doppler plane with pre-processing. Then, a two-dimensional CA-CFAR is used to remove noisy data, and the result is given to a clustering block with the mean shift algorithm. During this process, the information related to the target is placed in a cluster. The information of each cluster is entered into the classification block to judge whether it is a target or not. Nieman-Pearson criterion and Kalbeck-Lebler divergence function were used for the classification block.

In [13] Yongzhen et al uses the information in the data with different polarizations. To have data with all polarizations, the radar transmitter and receiver must have the ability to separate data into two polarizations V and H. Then, using polarimetric analysis of correlation and dispersion matrices, features are extracted. These features are independent of each other and contain distinctive information target and chaff. The obtained features are entered into a support vector machine for classification and a judgment is made wheter the signal is target or chaff.

It should also be noted that [14] is a suitable reference for investigating the methods in which artificial intelligence that has been used in radar. Artificial intelligence has been used in the field of radar waveform and antenna array design, waveform detection, automatic target recognition, and dealing with interference. The figure below illustrates this.

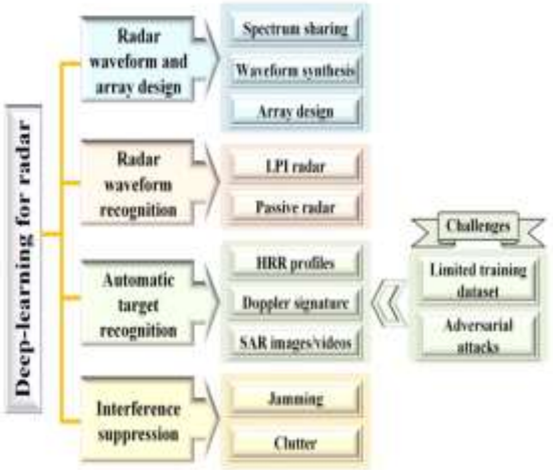

Fig. 3. Areas of application of artificial intelligence in radar [14].

The upcoming research is related to waveform design and automatic target detection from the above diagram.

3. SYSTEM MODELING AND SEPARATION METHODS

3.1 Target detection algorithm from chaff using symmetry

First, it is necessary to select the desired target signal range from the total received signal. For this purpose, in [8], the constant false alarm rate (CFAR) method was chosen to detect the target location. Then the noise level of the signal outside the target range (in other words, the background noise) is extracted and finally the whole signal is compared with the threshold level which is proportionate of the noise level. In the next step, using the maximum distance obtained with a threshold level proportional to the length of the target, the signals related to each target are clustered and finally S_m (n) is obtained. Finally, the symmetry criterion for this S_m (n) is obtained. Therefore, the steps of the algorithm can be expressed in the following order.

Step 1. Extracting the received signal maxima using CFAR, removing the target from the receiving gate and calculating the background noise level of the remaining signal and calculating the target threshold level.

Step 2. Extract the signal from the receiver gate using the target threshold level

Step 3. Clustering the maxima extracted from step 2 and forming S_m (n)

Step 4. Calculation of the symmetry criterion ξ_m for S_m (n)

Step 5. Separation of ξ_m in the following order:

$$\begin{cases} \xi_m > Th_\xi & ship \\ \xi_m \le Th_\xi & chaff \end{cases} \quad (1)$$

where 〖Th〗_ξ is the threshold level of discrimination between target and chaff.

3.2 The feature of the average Grey correlation degree (AGCD)

Target returns in successive pulses have higher correlations than chaff. Therefore, the time domain features can be used to identify the chaff. Some methods directly use waveforms for increasing correlation. Here, the better the resolution of the radar, the better the performance quality of the method. The correlation of Chaff is lower than the target and as a result the correlation coefficient between the return waves is weaker than that. The figure below shows the autocorrelation function of the cloud samples obtained from the real X-band radar.

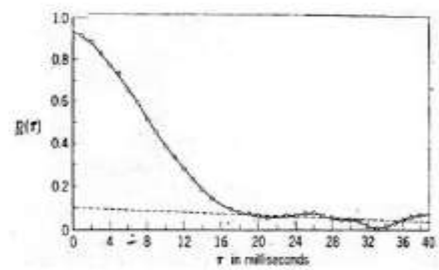

Fig. 4. Autocorrelation function of Chaff cloud samples.

In [5], for final guidance radars, the average gray correlation criterion of AGCD is presented, which shows the characteristic difference in temporal correlation between the target and the chaff.

Based on grey theory, degree of correlation (GCD) is a measure of similarity between two signals [4]. In other words, GCD between two returned sequences shows their similarity. It is clear that the return correlation time of the chaff is lower than that of the target because the inter-correlation of the chaff is much lower than the target. As a result, GCD can be a suitable criterion for distinguishing chaff from target. This criterion can be effective in the phases of growth, maturity and fall of chaff. To obtain the AGCD criterion, the following procedure is used. We consider the return signal in pulse i as follows:

$$X_i = (x_{i.0}.x_{i.1}.''' .x_{i.N}) \quad (2)$$

And in this case, the GCD between two consecutive pulses is considered in the following order:

$$\alpha_i = \alpha(X_i.X_{i+1}) = 2\left(\frac{1+|X_i|+|X_{i+1}|}{1+|X_i|+|X_{i+1}|+|X_i-X_{i+1}|}-\frac{1}{2}\right) \quad (3)$$

where in:

$$X_i = \left|\sum_{k=1}^{N-1} x'_{i.k} - \frac{1}{2}x_{i.N}\right| \quad (4)$$

$$|X_i - X_{i+1}| = \left|\sum_{k=1}^{N-1}(x'_{i.k} - x'_{i+1.k}) - \frac{1}{2}(x_{i.N} - x_{i+1.N})\right| \qquad (5)$$

And

$$x'_{i.k} = x_{i.k} - x_{i.0}\ for\ k = 1.2.'''.N-1 \qquad (6)$$

Using the above definition, we see two features of GCD. First, 0<α_i≤1 and second, α_i is independent of the transformation. For M pulses, M-1 GCD value is obtained, which is considered as α= (α_1. α_2. ^"‘. α_(M-1)). In order to reduce the effects of noise, the average value of GCD or in other words AGCD is used.

$$\bar{\alpha} = \frac{1}{M-1}\sum_{i=1}^{M-1}\alpha_i \qquad (7)$$

In order to calculate the appropriate threshold level of AGCD for chaff detection, in [5] due to the lack of sufficient data for measurement, ground clutter AGCD has been used. Meanwhile, here, using the simulation information in [9], the appropriate threshold level value for AGCD is obtained.

3.3 Doppler spread feature

The behavior of the return signal from the target and chaff is different in the Doppler domain. Since chaff particles spread in space at different speeds and move irregularly due to wind, the dispersion in the Doppler field for chaff is more than the target [9]. Doppler processing is used to extract this feature. In this way, the samples related to a range cell are taken to the Doppler domain using fft transformation. Then the width of each peak will determine the Doppler spread for that signal. The figure below shows how to extract this feature. The width of each peak is considered as the Doppler spread.

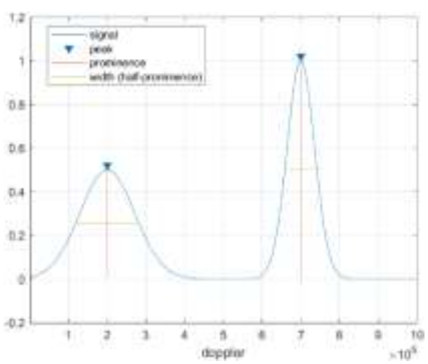

Fig. .5. Doppler spread feature extraction.

4. SUGGESTED METHOD

To distinguish the target from the chaff, we need distinctive features that can make a proper distinction between the target and chaff. These features can perform differently in different working scenarios such as waveforms, working frequencies and weather conditions. The solution presented here is based on a cognitive radar system that, according to the feedback from the environment, adjusts its working parameters in a way that makes the most distinction between the target and the target. For this purpose, the emphasis is on choosing the suboptimal waveform from a set of waveforms. In this way, the waveform sent by the radar is determined adaptively according to the defined criteria in separating the target from the chaff.

The proposed design approach for this is the use of deep neural network with appropriate pre-processing. In this way, first the received radar signal is pre-processed to obtain the appropriate feature vector in separating the return signal of the target from the chaff. The output of the neural network determines the success or failure of each waveform in separating the chaff from the target. In this way, the radar intelligently decides what the optimal waveform will be used in the next moment according to the received signal at the current moment.

5. CHAFF DETECTION NETWORK OF THE TARGET IN THE RADAR

To deal with Chaff, the cognitive radar technique has been used to distinguish Chaff from the target. In this way, according to the signal received from the environment, the waveform sent by the radar is changed and then in the receiver, it is distinguished from the target by using the provided features. But the simulations show that the features presented above alone, cannot perform well in all scenarios in detection the target. To solve this issue using artificial neural network, a network for detection of the target has been implemented. This network offers the possibility of distinguishing between the target and the chaff with better accuracy than the features introduced above. In this way, the received signal is pre-processed first. When pre-processing is done, target detection features are extracted from Chaff, namely AGCD, symmetry, Doppler spread for the peaks found in the signal. Then, this feature vector is entered into the deep neural network so that according to it, the presence and absence of the chaff and the separation of the chaff from the target can be done.

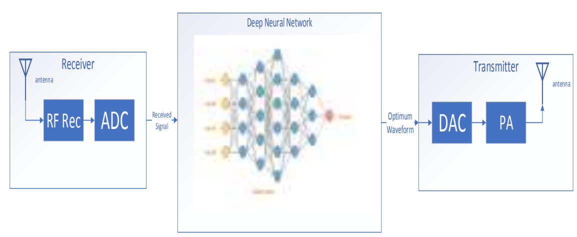

Fig. 6. Block diagram of neural network.

6. DEEP NEURAL NETWORK ARCHITECTURE

As mentioned, the features obtained in the pre-processing stage should be entered into the deep neural network to judge the appropriateness of the sent waveform. The main layer in this architecture is a fully connected layer that is placed in four sequential layers.

After each fully connected layer, a relu activator layer is placed. The presence of the activation function in each layer of the neural network is mandatory. Because each classification layer in the neural network is a linear operator. In order for two linear operators not to be reduced to one layer, it is necessary to place a non-linear layer like the activation layer between them. Also, at each layer, the data is normalized before entering the fully connected layer. Data normalization improves the convergence of the training process to the desired answer. The number of neurons used in the layers also has a decreasing trend. Experimentally, it has been found that if the number of neurons of layers have a decreasing trend, the network convergence will be better. The reason for this is that the initial layers extract the desired feature from the data and by passing through each layer, the data becomes more abstract until finally the data goes to the last layer and the cost function is applied on it. The structure of the neural network is considered as follows.

Fig. 7. Neural network structure

It should be noted that the Dropout layer is only present during training. This layer prevents overfitting the network on the training data. The general function is to turn off some neurons randomly. The block diagram of the network is as follows.

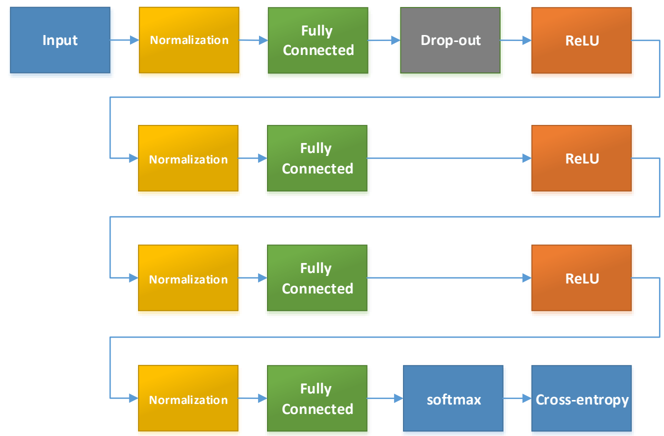

Fig. 8. Block diagram of deep neural network.

The number of parameters under training is as follows.

Table 1. Block diagram of neural network training for target recognition from chaff

Learning Parameters	No of Activation Layer	Layer Type	Layer Name	#
-	۶	Input Char	Input	۱
Offset ۶*۱ Scale ۶*۱	۶	Batch Normalization	BN_1	۲
Weight ۱۲۸*۶ Bias ۱۲۸*۱	۱۲۸	Fully Connected	Fc_1	۳
-	۱۲۸	Dropout	Drop_out	۴
-	۱۲۸	ReLU	Relu_1	۵
Offset ۱۲۸*۱ Scale ۱۲۸*۱	۱۲۸	Batch Normalization	BN_2	۶
Weight ۶۴*۱۲۸ Bias ۶۴*۱	۶۴	Fully Connected	Fc_2	۷
-	۶۴	ReLU	Relu_2	۸
Offset ۶۴*۱ Scale ۶۴*۱	۶۴	Batch Normalization	BN_3	۹
Weight ۳۲*۶۴ Bias ۳۲*۱	۳۲	Fully Connected	Fc_3	۱۰
-	۳۲	ReLU	Relu_3	۱۱
Offset ۳۲*۱ Scale ۳۲*۱	۳۲	Batch Normalization	BN_4	۱۲
Weight ۲*۳۲ Bias ۲*۱	۲	Fully Connected	Fc_4	۱۳
-	۲	Softmax	Softmax	۱۴
-	۲	Classificaion Output	Classoutput	۱۵

To train the network, the parameters are considered in the following order.

• Adam's solver with gradient drop rate parameter equal to 0.7

• Piecewise learning rate with decreasing value every 50 epochs

• 30% dropout rate

• L2 regularizer

Adam's method is an optimization algorithm to optimize the performance of the gradient descent (GD) algorithm. This method is efficient when working with large problems that contain many data or parameters.

This method requires relatively less memory and is more efficient. Intuitively, this method is a combination of "gradient descent with momentum" algorithm and "RMSP" algorithm.

7. WAVEFORM SUGGESTION NETWORK

As mentioned, in order to recognize which waveform is appropriate, it is necessary to have a network that can suggest the appropriate waveform for the next moment. For this purpose, since the time process of changing environmental conditions and the selection of waveforms are important, LSTM network is used. This network receives information about how to select waveforms sequentially as input and produces its proposed waveform as output. The order of placing the layers is as follows.

Fig. 9. Waveform proposal network layers.

The general structure of this network is that first, the input data that includes the waveform code selected at any moment enters the network in order. Then, in the first step, the data is entered into LSTM layers. Then the output of this layer enters a fully connected layer to be ready for use in the output regression layer. Finally, the network cost function is formed according to the regression layer. The output of the network is responsible for generating the appropriate waveform code. It should be noted that the Dropout layer is used in the training process in order to prevent data overfitting. The block diagram of the network is as follows.

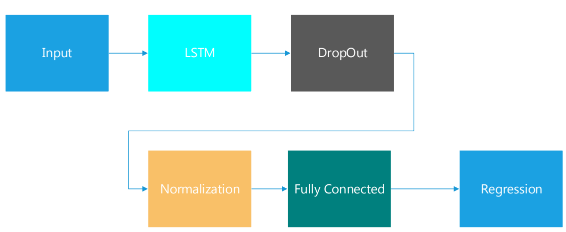

Fig. 10. Block diagram of the proposed waveform network.

The number of network parameters is according to the table below.

Table 2. Block diagram of neural network training for waveform suggestion

Learning Parameters	No of Activation Layer	Layer Type	Layer Name	#
-	۱	Input Char	Input	۱
Input Weight۱۶۰*۱ Feedback Weight ۱۶۰*۴۰ Bias۱۶۰*۱	۴۰	LSTM Feedback	LSTM	۲
-	۴۰	DropOut	DropOut_1	۳
Offset۴۰*۱ Scale ۴۰*۱	۴۰	Batch Normalization	BN_1	۴
Weight۱*۴۰ Bias۱*۱	۱	Fully Connected	Fc_1	۵
-	۱	Regression	Regression Output	۶

The hyper parameters of the network are as follows.

• Adam's solver with gradient drop rate parameter equal to 0.5

• Initial learning rate equal to 0.05

• Piecewise learning rate with decreasing value every 50 epochs

• 50% dropout rate.

8. DATASET GENERATION AND NETWORK TRAINING

As mentioned, the neural network architecture is designed in such a way that the feature vector obtained from the received signal is given as an input to the network. The network output also shows whether or not the usage waveform is suitable. In this way, a database should be produced that has such a structure. It means that a set of signals has been generated and then the feature vector related to each one has been extracted. Finally, the output label of the network is considered as whether the considered waveform is suitable or not. The considered dataset includes all scenarios and all waveforms.

9. SIMULATION

9.1 Waveforms

The waveforms used in the simulation are as follows:

Table 3. Waveforms used

Parameters	*Waveform*	*#*
-	*LFM*	۱
-	*NLFM*	۲
۱۱	*Barker*	۳
۳	*Frank*	۴
۹	*P1*	۵
۴	*P2*	۶
۹	*P3*	۷
۹	*P4*	۸
۹	*Px*	۹
۱۶	*Px*	۱۰
-	*Stepped LFM*	۱۱

10. SCENARIOS

The scenarios of environmental conditions used in the simulations are obtained by changing the following parameters.

- Target speed
- Chaff speed
- Chaff time constant
- wind speed
- Sigma shear factor
- Sigma turbulence factor

For each of the above six parameters, two values are considered, which ultimately forms 64 different scenarios.

Table 4. Parameters of the scenarios.

Dimension	Qty	Parameter
m/s	۱۵ ۵	Target Velocity
m/s	۱۰- ۵-	Chaff Velocity
S	۰,۰۱ ۰,۰۵	Chaff Time Constant
m/s	۵ ۱	Wind Speed
-	۰,۰۵ ۰,۲	$Sigma_{shear}$
-	۰,۰۱ ۰,۱	$Sigma_{turb}$

To model different scenarios, different values of scenario simulation parameters are considered and finally 64 scenarios are considered.

The figures below compare different methods for separating the chaff from the target.

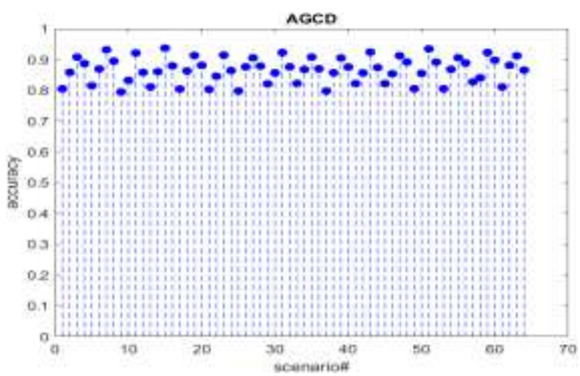

Fig. 11. The accuracy of AGCD for different scenarios.

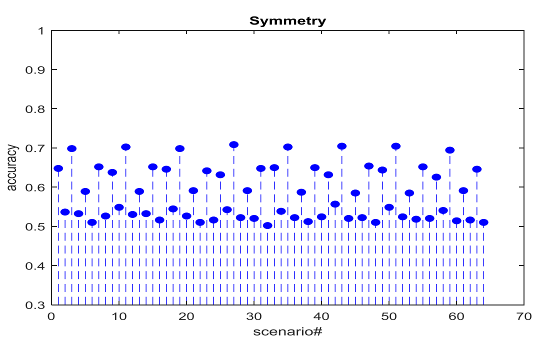

Fig. 12. The accuracy of Symmetry for different scenarios.

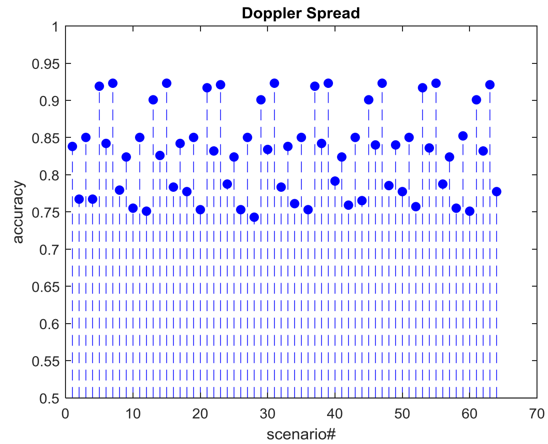

Fig. 13. The accuracy of the Doppler spread for different scenarios.

As can be seen in the graphs, the AGCD feature performs better than the symmetry and Doppler spread features. But in some scenarios, this function has low accuracy. In order to improve this function and improve the accuracy in distinguishing the target from the chaff, using the presented neural network, the accuracy of distinguishing the target from the chaff is obtained according to the following diagram.

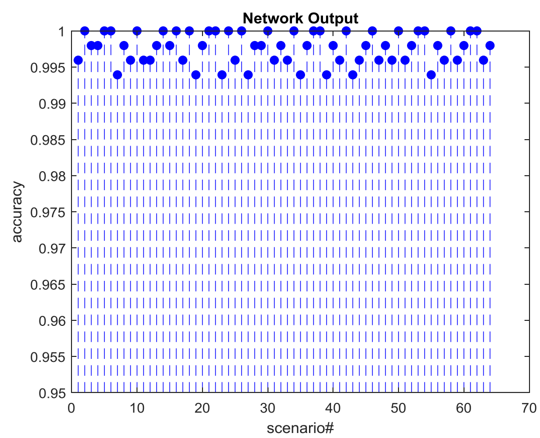

Fig. 14. The accuracy of the deep neural network for different scenarios.

We can see that the output performance of the neural network has provided a significant improvement compared to the performance of individual features in separating the target and the target. The figure below shows the accuracy of each method side by side.

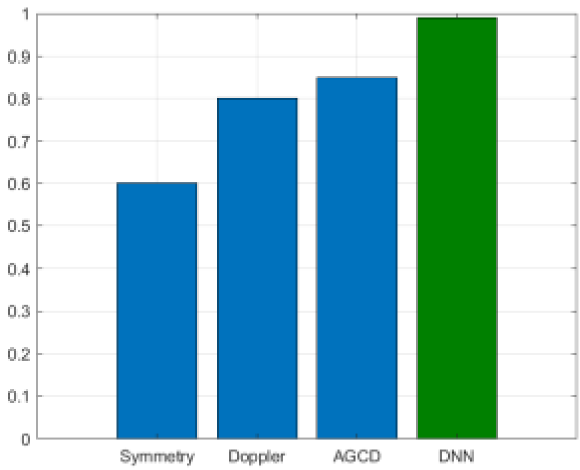

Fig. 15. Comparison of accuracy of different methods.

As can be seen, the proposed method performs better.

11. WAVEFORM SUGGESTION NETWORK

The designed network for waveform suggestion is trained in this section using the designed database. The label of each data is equal to the waveform that has the ability to distinguish between the target and chaff. Since the architecture of this network is based on regression, the cost function for training the network is RMSE. The figure below shows the network training process.

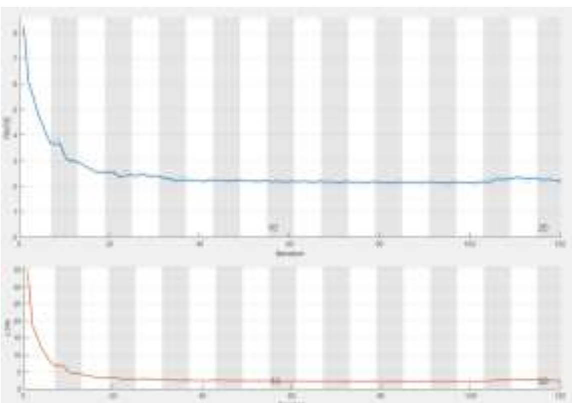

Fig. 16. The training process of the waveform suggestion network.

As can be seen, the network training process is such that the cost function decreases uniformly. To verify the appropriate performance of the network, a part of the generated database data is considered as test data and the network performance is checked on them. The accuracy of the network on the test data is equal to 91.3.

12. CONCLUSION

In this article, we investigated the challenge of target detection from chaff in target tracking radars. We have studied the various features that have been reviewed in the articles to detect the target from the chaff and we have observed that these features alone cannot provide optimal accuracy in all the considered scenarios. Next, in order to improve the target detection performance of Chaff, artificial neural network is used and it has been observed that this network can improve the performance of the best features used in different scenarios and thus provide a new solution to deal with Chaff.

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