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Radar Target Detection by Using Levenberg-Marquardt Algorithm

Abstract. *Typically, with radar systems, a person is required to assist in the process of detecting a target. As a result of this human factor, radar systems are not completely dependable since their performance differs across operators. In this work, an intelligent radar system for border monitoring is described. Artificial neural networks trained using the Levenberg-Marquardt technique have been used to identify and categorize targets automatically in the radar system under development. Inverse Synthetic Aperture Radar images captured with high resolution by the radar's detecting module serve as both input and output data for the neural network. The simulation findings show that intelligent radar can identify various targets. Both human operators and a competing radar system were no match for the radar's efficiency.These findings suggest that in the future, intelligent technologies may be able to take the position of human radar operators in high-risk security environments.*

Streszczenie. *Zazwyczaj w przypadku systemów radarowych wymagana jest osoba do asystowania w procesie wykrywania celu. W wyniku tego czynnika ludzkiego systemy radarowe nie są całkowicie niezawodne, ponieważ ich wydajność różni się w zależności od operatora. W pracy opisano inteligentny system radarowy do monitorowania granic. Sztuczne sieci neuronowe wyszkolone przy użyciu techniki Levenberga-Marquardta zostały wykorzystane do automatycznej identyfikacji i kategoryzacji celów w opracowywanym systemie radarowym. Obrazy radaru z odwróconą syntetyczną aperturą zarejestrowane w wysokiej rozdzielczości przez moduł wykrywający radaru służą zarówno jako dane wejściowe, jak i wyjściowe dla sieci neuronowej. Wyniki symulacji pokazują, że inteligentny radar może identyfikować różne cele. Zarówno operatorzy, jak i konkurencyjny system radarowy nie dorównali wydajności radaru. Odkrycia te sugerują, że w przyszłości inteligentne technologie mogą zająć miejsce operatorów radarów w środowiskach wysokiego ryzyka.(Radarowe wykrywanie celu za pomocą algorytmu Levenberga-Marquardta)*
(Wybór procedury optymalizacyjnej dla systemu CAD)

Keywords: Doppler information, high range resolution, surveillance, automatic radar target recognition, Neural Networks
Słowa kluczowe: Please define Polish key-words using \slowakluczowe command.

Introduction

It is common for radar systems to be able to identify and track targets without the need for human intervention, although this is not always the case. Radar systems can't be relied on in these situations since operators' performance fluctuates so much[1][2][3]. In order to improve and stabilize the performance of a radar system, the addition of autonomous detection and identification capabilities is a need. Human operators will no longer be required to make important decisions for the system presented in this study. By integrating a cognitive engine, neural network, and radar, it is possible to construct an intelligent radar system that can perform like a human operator with years of expertise [4][5]. As a result of his fascination with the bat's echolocation mechanism, Simon Haykin pioneered the concept of intelligent radar in
[6][7]. Radar networks with intelligence were added to the concept in[8]. This system has the capacity to maintain environmental data far better than individual radar components can alone. Cognitive radar for distant sensing was first reported in 2012[9].

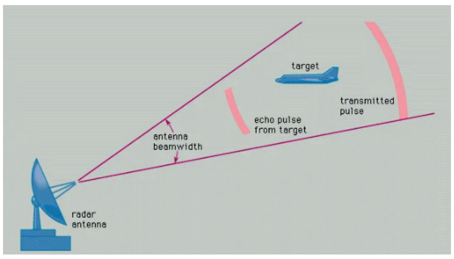

Fig. 1. Concept of a radar's signal

There have been earlier studies on detection and tracking and target identification[3][10], but the challenge of automatically recognizing items often found in a border monitoring scenario that includes a desert has never been investigated until this work. It is necessary to construct radar systems that can improve the capabilities of border patrol officers, surveillance operators, and command staff in order to guarantee the protection of this vital area. In the absence of suitable sensors and cameras, designing systems that can identify threats at a fair pace without overburdening the entire monitoring system with false warnings is critical. The research given in this article might assist to reduce the difficulties faced in this critical national security setting, which includes human, vehicle, and low-flying Cessna Airplanes as the targets of study. Furthermore, Among the few recent publications, this is an important addition to the investigation of radar target classification across various transportation settings., in this case, land and air.

How a common radar system operates will be covered in more detail in the subsequent section. In Section II, we look at an abstract neural network for classifying radar targets. Section III reports the findings of an automated classification simulation utilizing an artificial neural network, based on the radar detection of typical border surveillance targets.

Overview of the intelligent radar system

0.1 Detection of Radar Targets

First, radar transmits an RF signal, which is analyzed and processed to determine the target's range, velocity, and direction. A person, car, or other moving object may be detected, located, and identified with radar[11][12]. There are three different modes of operation that the radar can perform: initial target detection ,Doppler ,high-resolution, inverse synthetic aperture radar . Before the neural network can utilize the high-resolution pictures for recognition, it has to be able to switch modes on the radar to get the best possible results. If anything is to be found in the immediate area, Mode 1 should be tried first. Once a target has been located, keeping tabs on its rate of travel is crucial. When operating in Mode 2, the radial speed of the target may be calculated using Doppler theory, which postulates that the speed of an object has an effect on the frequency of the returned signal. To calculate the target's speed, the system should transition between Modes 3 and 2 depending on the Doppler shift of the reflected signal. Mode 3 imaging, which uses high-resolution range profiles as its hallmark, has the potential to provide a high-resolution, two-dimensional image of an item of interest. Given that the targets are assumed to be traveling quickly enough for Mode 3 to be used, Mode 2 is not described here. In what follows, we'll examine the study's extensive usage of many operating modes in further detail.

0.2 Preliminary Determination of the Target (Mode 1)

Radar's most basic challenge is locating a target. This involves identifying whether or not either an echoed reflection or random noise are the receiver's outputs. To identify the targets of interest, this mode employs the moving target indicator concepts. Targets that are stationary or slow-moving can be identified by the moving target indicator.The radar receiver employs an envelope detector in conjunction with a threshold judgment in order to assess whether or not a target has been identified once the target has been located. additive zero-means white Gaussian noise and The target radar signal are the two components that make up the return signal. The return signal is characterized in terms of the input signal that is sent to the receiver.

$$r(t) = n(t) + s(t) \tag{1}$$

Where $s(t) = sin(\omega_0 t)$ stands for the signal that is being broadcast, $n(t)$ refers to the white Gaussian noise $\omega_0 = 2\pi f_o, f_o$ represents the frequency There are two possible outcomes for target detection: either the target exists or it does not [13][14]. When $r(t)$ hits the threshold value,V_T, the presence of a target may finally be identified. The following are the two outcomes that are conceivable as a result of the process of decision making:

$$Hrt = nt \qquad Notargetdetected$$

$$H = rt = st + nt \qquad Targetdetected \tag{2}$$

The receiver must choose a hypothesis that has a high likelihood of being right. As much as possible, a target should be recognized even in the presence of noise, but the goal is to minimize the possibility of an incorrect target declaration being made by the receiver.
"Maximizing the probability of detection" refers to the process of estimating how much of a signal a receiver should be able to pick up on a target even when there is background noise present [15] .

$$P_d P(D_0|H_1) = \int_{V_T}^{\infty} P_1(r)dr \tag{3}$$

The Neyman-Pearson threshold can be used to indicate the lowest possible likelihood of a receiver missing a target by announcing the presence of a target in the presence of only noise. False alarms are described in (4), and the threshold can be used to indicate the lowest possible likelihood of a receiver missing a target.

$$P_{fa} P(D_1|H_0) = \int_{V_T}^{\infty} drP_0(r) \tag{4}$$

These two conditional probabilities are connected to one another. When these numbers are expressed in terms of the decision area and the probability function, the decision rule may be derived from that expression.

$$V_n = \frac{P_1(r)}{P_0(r)} \begin{matrix} > \\ < \end{matrix} V_T \tag{5}$$

p_1 and p_0 are the prior probability for the data given hypotheses 1 and 0, respectively, and V_T is the threshold value, respectively.
You should realize that decreasing the detection threshold and therefore raising P_d leads in a rise in the P_{fa}. In order to achieve the goal of increasing P_d, a likelihood ratio test is used.
A time delay τ is displayed in Figure 1 when the transmitter emits a signal that reaches the target and is reflected back to the transmitter. It is possible to estimate the target's distance by comparing the sent $s(t)$ signal with the resulting returned signal $r(t)$. In equation (6), the signals are shown.

$$s(t) = sin(2\pi f_0 t) \tag{6}$$

$$r(t) = n(t) * \sigma + sin(2\pi f_0(t - D)) \tag{7}$$

The cross-correlation function between received signal and the broadcast signal is often compared to calculate the time delay. This is shown in the equation below (8). Whereas $n(t)$ the zero-mean white Gaussian noise and D is the delay in the signal's trip from the transmitter to the target.

$$R_{rs}(\tau) = \int (t - \tau) * r(t)rdt \tag{8}$$

Equation (9) is used to calculate the target's range.

$$R\frac{c\tau}{2} \tag{9}$$

Light travels at a constant speed of $c = 3 * 108$ meters per second (m/s), hence the target's range is equal to $3*108$ meters per second (m/s). Because of the two-way delay, a factor of 12 is required.

where R denotes the distance to the target, c stands for the speed of light, $c = 3 * 108\ m/s$, and denotes the amount of time that has elapsed. The delay in both directions requires a factor of one-half to be applied.

In order to begin the process of range processing, The incoming signal must be filtered before further processing can occur. This is done to reduce the influence of any noise that may have entered the signal. The optimum method for filtering the signal is to use what is known as a "matched filter" to the original signal. then need to know how long it takes for the signal to be sent out and then received so that can calculate its range. Using the equation, one may determine how far they are from reaching their objective.

0.3 The Doppler Effect is a kind of amplification (Mode 2)

Doppler principle used in this study which states that the frequency of the return signal is modified by the speed of a moving object, it is feasible to calculate the radial speed of the target in a direct manner. According to, the Doppler frequency is able to determine the radial velocity of the target, which allows it to differentiate between moving and stationary objects. When an item is traveling at a certain speed, the signal that is reflected back will have a frequency that is different from the frequency of the initial signal. A Doppler shift is the name given to this phenomenon because of the difference in frequency. The Doppler shift may either be negative or positive , depending on what the target is moving in the direction of the radar or away from it. When the radar signal is reflected off of an object that is moving toward the radar, a signal that is more tightly packed and has a higher frequency is created. When trying to keep up with a target that is moving away from the radar, you will need to reduce the frequency of the radar.

$$r(t) = e^{j2\pi f_d (t-\tau_0)} s(t-\tau_0) \tag{10}$$

In this case, τ_0 is the goal delay and f_d is the Doppler shift. Sending and receiving signals are evaluated for frequency shifts using the Fourier Transform (FT) and spectrograms of the two signals[16]. Doppler effect is clearly seen in the spectrum's frequency range. Doppler shifts in frequency and time may be converted to velocities using the carrier frequency and the speed of light.

$$f_d = \frac{2v}{c} f_c \tag{11}$$

Light speed c and Doppler frequency shift f_d. The equations where f_c is the carrier frequency If the radar line of sight and the target are at an angle, then the radial velocity may be calculated as $2vcos\theta$, where θ is the entire angle.

$$f_d = \frac{2vcos\theta}{\lambda} \tag{12}$$

Target velocity must be calculated when range and detection have been established. If there is motion, then the processing of velocity is based on the difference in frequency. That frequency shift is known as the "Doppler shift" while traveling at high speeds. The Doppler shift in frequency used to calculate the object's speed. Unless the item is moving at a very high velocity relative to the speed of light, the Doppler shift will be negligible and hard to detect from a single pulse. Therefore, a signal with periodic pulses must be sent in order to quantify the Doppler effect.
Doppler shifted reflected signals may be used to calculate goal velocity, and then the system can automatically switch between different operating modes based on the output velocity. A high-resolution mode or an Inverse Synthetic Aperture Radar (ISAR) mode may be activated based on the speed of the target and the current mode.

0.4 Radar that uses inverse SAR (Mode 3)

Inverse synthetic aperture radar (ISAR) is an imaging technology that generates high-resolution 2D images of the target by using complex signal processing algorithms. ISAR is a kind of SAR that may be used to capture images of moving targets, such as aircraft. ISAR processing techniques are employed when high-resolution images of an object are required. It achieves this by sending out a signal and measuring how strong the response was. If the pulses are being emitted at an angle, as seen by a darker region in the scattering image, then very little of the signal will be returned to the radar.

Table 1. Descriptions and attributes of the three targets

CHARACTERISTICS	DESCRIPTION	Value
Detection:Land targets	people	RCS $= 1m^2$
	Vehicle	RCS $= 5m^2$
Detection ranges:Air targrts	Cessna	RCS $= 10m^2$

Images are made and processed employing MATLAB macros. Treating the target as a set of point scatterers simplifies the modeling process. As a result, the radar's range and the strength of the reflected signal define the properties of each scatterer. There is a positive relationship between the number of point scatterers and the Radar Cross Section (RCS), which is also affected by the radar's angle of incidence.
A stepped frequency waveform of M bursts is used in Mode 3 to create a pulse matrix, with each burst consisting of N stepped frequency signals. To calculate the frequency of the nth pulse in a burst, the following equation was employed

$$f_n = f_0 + n\Delta f \tag{13}$$

A burst of pulses has a starting frequency of f_0 and a stepping frequency of Δf. It defines the radar system's capacity to distinguish one target from another based on the distance between them and is described as range resolution.

$$\Delta r = \frac{c}{2B} \tag{14}$$

Slant range resolution is defined by the equation if N pulses are stepped in frequency by f. (15)

$$\Delta r = \frac{c}{\Delta f 2(N-1)} \tag{15}$$

The solution to this equation allows us to model the process of image construction, which speeds up the process significantly. A matrix with $m\ x\ n$ and n columns depicts the range-Doppler, which may be the ISAR image of the objects. In order to construct the picture, we take the transfer function to be the total of the steady-state responses of the active regions.:

$$H = \sum_{1}^{n} A_L e^{i2\pi f T_L} \tag{16}$$

where H is the sum of phasors and $T_L = 2R_L/c$, $A_L = 1$.

The reflectivity of the target may be determined as a function of time by getting the Inverse Discrete FT, often known as the IDFT. The RCS of the scatterer, as well as its position, may be obtained via the use of the IDFT. The table 1 provides a summary of the usual attributes and descriptions of the three objectives.
When categorizing the targets, The target shape is represented in a parametric form as a feature set. Each row of the matrices $H(k,j)$ must have its IDFT calculated. After the IDFT has been calculated for each column of data, the discrete Fourier transform (DFT) is immediately performed.

$$h(n,k) = \sum_{j=1}^{N-1} e^{i2\pi f/N} H(k,j) \tag{17}$$

The O/P pictures will be represented by the function $D(n,m)$, which has the form.

$$D(n,m) = \sum^{M-1} e^{-i2\pi m/M} h(k,n) \tag{18}$$

ISAR is a method that can provide a detailed flat image of a target. After that, the created matrix will be fed into a neural network in order to classify the targets.
This paper describes an examination of many operational

modes for radar systems, but it does not look at methods for seamlessly shifting between these modes over the course of object detection and classification. Fuzzy logic, which will be studied in the future and used to model the rules necessary to carry out these complex decisions intelligently, will be the strategy used to overcome this problem. Since fuzzy logic has been proved to be useful in a variety of contexts, including the decision-making process for categorization challenges, it seems to be a promising approach.

0.5 Neural Networks for the Purpose of Target Recognition

Cognitive radar's use here is to create a smart system that can not only see and identify targets, but also place them into predetermined classes. As a direct outcome of this research, a surveillance radar capable of distinguishing between human beings, automobiles, and Cessna aircraft will be constructed.

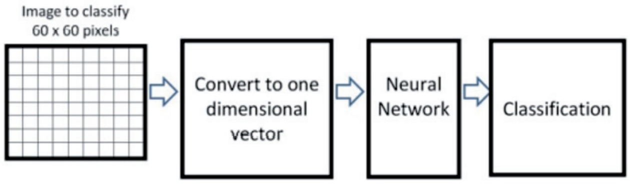

Fig. 2. Concept of a radar's signal

Table 2. Radar System Parameters

Symbol	Description	Value
τ	Delay	2 sec
t	Sampling period	0.001
N	Number of samples	1024
f_0	Carrier Frequency	50 Hz
F_s	Sampling Frequency	1000 Hz
A	Amplitude	1 V

In order to properly categorize the targets, we will employ a neural network that has been trained on high-resolution images of these categories. Due to the fact that neural networks have been shown to accurately categorize objects based on noisy pictures, they may be used to achieve automated recognition. Numerous instances of neural networks being used to control sophisticated electro mechanical devices have been documented.
Interconnected artificial neuronal networks that utilize a computational model to process information and execute meaningful computations via learning are the definition of a neural network.
Inter neuron connection strength, or synaptic weights, are used to store the information gained. In order to complete the learning process and achieve a desired design aim, a learning algorithm is employed to modify the synaptic weight of the network in an ordered method. A neural network is used to identify the kind of item being detected by the radar once the best operating mode has been found.
The k^{th} neuron's output is determined by

$$y_k = \phi\left(\sum_{j=0}^{p} W_{kj} x_j\right) \tag{19}$$

where the synaptic weights of neuron k are represented by the synaptic weights of neuron k's synaptic weights ϕ.

Figure 2 depicts the model of a neural network used in this study to categorize the various targets. For this model, a feed-forward neural network is used. The hidden layer has 60 neurons and the transfer function is represented by an eigenvalue of the function of the output layer, which is a tangent sigmoid. Before being transmitted to the neural network, the truck ,Cessna and people's photos are converted from two dimensions to a single vector. In each input vector, there is only one target value. It is the categorization of the target presented in the 2D picture that serves as the target result.in the fig 3 below have been shown a cross correlation in radar

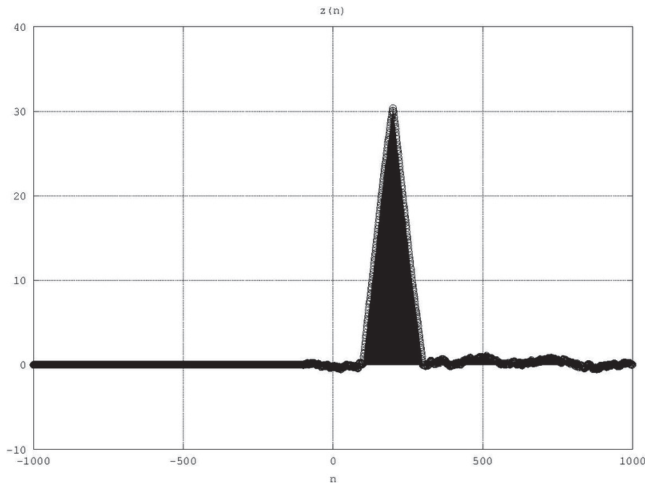

Fig. 3. cross correlation in radar

Results

0.6 Results of a Radar Simulation for Detecting a Target

Humans and vehicles on the ground are considered to be inside the radar's field of view, while the Cessna aircraft is about five miles away. As a general rule, 20dB SNR is considered a suitable level. Because the targets are in the radar's line of sight, both the person and the vehicle have the highest possible Doppler frequency. For various modes of operation, the system employs a variety of standard and custom waveforms. As previously noted, it is presumed that the operating modes are correctly chosen to carry out the duty of target identification.
To simulate the detecting radar system, we utilized the values shown in Table 2. A sinusoidal signal was sent to the receiver to see whether it could detect the target. This signal was returned by the radar, albeit with a time delay and additional noise. In the event that a target was discovered, the time delay between the broadcast and received signals was used to establish the target's range.

Table 3. Accuracy in identifying each target class in the training set for a range of hidden neuron counts

Covert neuronal pathways	50	55	60	65
Truck	92%	98%	95%	100%
Plane	98%	95%	98%	91%
Pedestrian	59%	59%	95%	81%
Overall	83%	84%	96%	91%

In this study, we set out to create a radar system with a 98 percent detection rate and a 0.2 percent false alarm rate. This is the likelihood that a target was seen in the midst of a large amount of background sound. In order to find the target even when there is a lot of background noise, the false alarm rate was reduced. The signal-to-noise ratio

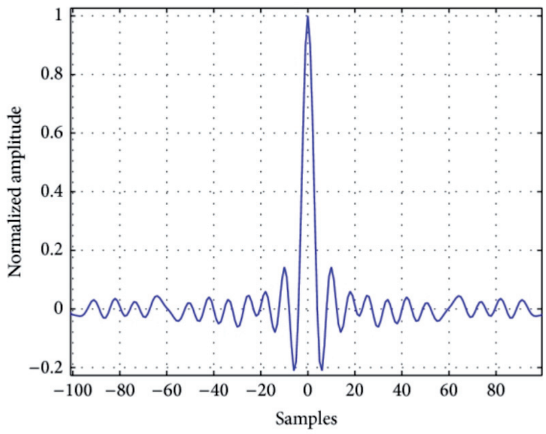

Fig. 4. The signal's autocorrelation

(SNR) was achieved in order to meet the performance requirements. The approach described below was used to successfully identify a signal generated during a MATLAB simulation.

Our last look at the radar's overall detection capabilities was in Section 3. Here, we present a thorough example of how to identify a single target using a single camera. In addition to clarifying Section II's radar theory, it will also assist to comprehend how the detecting components provide the information needed to feed the neural network in charge of identifying a target. Although the findings for a Cessna aircraft are provided in this section, they indicate the technique taken to identify various sorts of targets. Keep in mind that this strategy is simply one of numerous detecting methods, and the reader should keep this in mind while reading this material.

For a typical detection, the cross-correlation between the broadcast and received signals is depicted in Figure 3. Cross-correlation is shown in this graph, which is used to determine the range of the data points. Received and transmitted signals are illustrated in Equation as a cross correlation function .

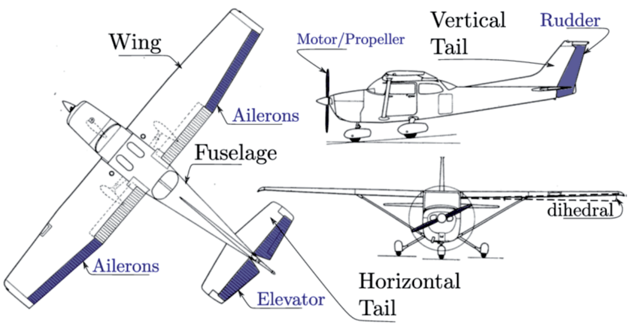

Fig. 5. The Cessna picture

The cross-correlation makes it possible to determine the even when there is a lot of background noise, the ability to detect the radar return signal. The presence of a significant peak in the cross-correlation function is evidence that the target detection simulation was carried out well and that the radar was able to identify the existence of a target. The location of the peak provides information about the target's distance from the observer.

then have been calculated the auto correlation of the signal by performing an inverse Fourier transform on the power spectral density of the return signal. This will give you the result. After conducting discrete time Fourier transformations

Table 4. Each of the target classes for the test sets has a classification

Real-Life Classification by NN	Truk	Plane	Pedestrian
Truck	84%	30%	15%
Plane	18%	72%	0.01%
Pedestrian	0.01%	0.01%	87%

on the spectra average time auto correlation of the signal realizations, the spectral was generated as a result. The procedure of breaking The strategy utilized in this investigation was to break a single signal into separate segments, correlate each segment. This calculation for the auto correlation is identical to that approach. Figure 4 presents the auto correlation of the return signal for your viewing pleasure. It has once again been shown that the modeling of the radar was effective, and that a target has been located thanks to the fact that the auto correlation has a single peak that can be noticed.

High range resolution required the presence of two features: 1) The frequency modulated signal's auto correlation required to have an origin spike as in Figure 4, and 2) the side lobes of the auto correlation had to be shallow and go out with increasing time lag.

Matching filtering was used to derive the range profile by simulating the broadcast pulse and applying it to the returning signal. High-resolution maps of faraway objects like landscape are provided by the inverse synthetic aperture radar (ISAR). An ISAR system was employed to give photographs of target objects, such as planes or automobiles on the ground. Each hot spot's range was calculated using an algorithm in order to mimic the Cessna's flight. Using the distance between each hot spot and the reference location, we were able to create a visual representation of the Cessna, as shown in Figure 5. FIGURE 6 depicts a 2D picture obtained by the ISAR of a Cessna aircraft.

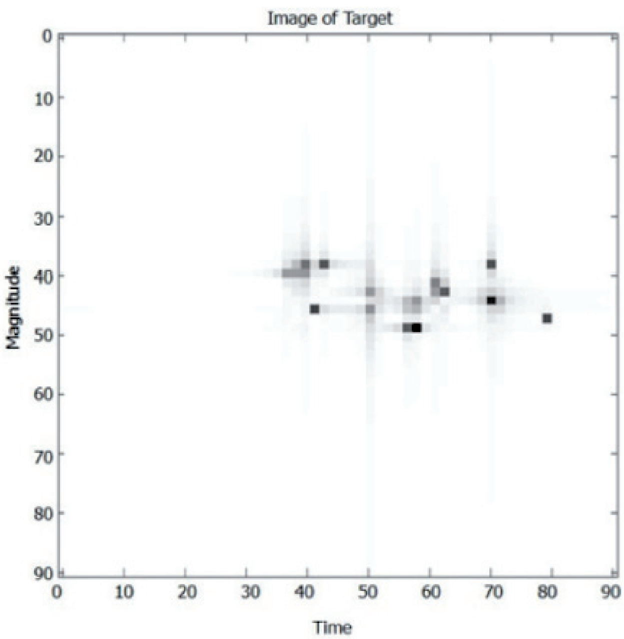

Fig. 6. 2D picture of a Cessna

0.7 Using Neural Networks to Identify Targets

A neural network in MATLAB was used to identify items based on the ISAR's 2D picture after the target had been identified using the information in Figures 3 to 6. The 3600

input data indicate the range profiles in a 60 by 60 matrix for each figure.

The neural network was trained and tested using a data set of 40 photos for each of the three object kinds. The signal-to-noise ratio for each picture is different. 17.5 percent of the data set was set aside for testing each of the three classes.

Due to its improved speed and performance over the standard back-propagation approach, the network trained using the Levenberg-Marquardt algorithm . MATLAB's Neural Network toolbox offers these training techniques, therefore it was unnecessary to write separate programs that implement them. For the neural network, a broad variety of potential hidden neurons was searched for in order to discover the ideal number. Though the number of hidden neurons in the first trials ranged from two to five to as high as 100, it was evident showed the best possible results could be obtained by placing the number of hidden neurons within the parameters outlined in Table 3. According to this table, the test set was determined to have 60 hidden neurons.

Table 4 shows the categorization results for several target kinds. The percentages of classifications that were right are shown in bold. A direct comparison with other approaches' proper categorization rates (Table 5) is impossible since this collection of targets has never been utilized before. More than 80% of the time, both land targets can be accurately detected. This is comparable to prior efforts that only focus on land targets. Another aspect that the neural network that was constructed for this research should have is the ability to ensure that pedestrians are never confused with cars and that researchers can only be confused with other land objects.

Table 5. Performance comparisons with various automated radar systems

Target	Performance
Flights on commercial planes	$97\% - 99\%$
Tanks	97%
People, animals, tracked or wheeled vehicles	$89\% - 97\%$
Armed vehicles	$89\% - 92\%$
Oversight of the border	81%
Pedestrians, aircraft, and watercraft	68%
All three types of road users (human performance)	40%

Even more crucially, the total performance is considerably better than both the human performance described [14] and the performance reported in [7] , which is the only other effort to incorporate both land-based and air-based items. They demonstrate both originality (the first time a border surveillance environment has been addressed) and that this paper's strategy and execution compare well with prior radar target categorization research efforts.

Conclusion

For the purposes of border monitoring, items such Cessna aircraft, vehicles, and people are often seen, therefore MATLAB was used to simulate a radar system that can broadcast and receive signals reflected off those objects. There was a lot of noise in the signals that were returned, making it impossible to locate the intended target. The cross-correlation of the returning signal provided the essential information to determine whether the target had been correctly identified. As a result of the ISAR approach, pictures of three distinct target types important to border surveillance in 2D high resolution were acquired by measuring the autocorrelation spectra.

The Levenberg-Marquardt approach was used to train neural networks that were then used to classify the photos. As a result, the suggested technique has the potential to reduce the issues associated with manned radar systems' lack of dependability by performing better than those achieved by human operators. In order to find the best approach for target categorization in this border surveillance scenario, additional research and comparison of neural network topologies and training methodologies are required before moving on to the next phase.

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