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Development of Scale and Rotation Invariant Neural Network based Technique for Detection of Dielectric Contrast Concealed Targets with Millimeter Wave System

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ABSTRACT

The detection of concealed targets beneath a person's clothing from standoff distance is an important task for protection and the security of a person in a crowded place like shopping malls, airports and playground stadium, etc. The detection capability of the concealed weapon depends on a lot of factors likes, a collection of back scattered data, dielectric property and a thickness of covering cloths, the hidden object, standoff distance and the probability of false alarm owing to objectionable substances. Though active millimeter wave systems have used to detect weapons under cloths, but still more attention is required to detect the target likes a gun, knife, and matchbox. To observe such problems, active V-band (59 GHz- 61 GHz) MMW radar with the help of artificial neural network (ANN) has been demonstrated for non-metallic as well as metallic concealed target detection. To validate ANN, the signature of predefined targets is matched with the signature of validated data with the help of the correlation coefficient. The proposed technique has good capability to distinguish concealed targets under various cloths.

Keywords: Millimeter wave; Correlation coefficient; Artificial neural network

1. INTRODUCTION

National Institute of Justice (NIJ), U.S. and the American Federation for Aging Research (AFAR) had funded to start research on concealed weapon detection (CWD) in 1995. Gradiometer metal detector, inductive magnetic field techniques, Electromagnetic resonances method, Terahertz (THz) imaging, millimeter wave (MMW) imaging and infrared (IR) imaging techniques have been used for the concealed weapon detection since 1995. Gradiometer metal detectors (GMD), based on passive samplings of the distortion of earth's magnetic field, has demonstrated for CWD application by many researchers[1-3] and reported that GMD is sensitive to metallic targets due to magnetic interference and insensitive to non-metallic targets such as, an explosive chemical. The inductive magnetic field technique has been demonstrated for CWD application[4]. This method is not able to detect low conductivity and small size material such as matchbox. Electromagnetic resonance is an active technique for detection of concealed weapons[5]. It uses radar cross section (RCS) as a signature to separate weapons and other objects. This method produces high rate of false alarm because of RCS of a person with a weapon is very similar to RCS of a person without a weapon. The Terahertz and infrared imaging techniques attract more attention of researchers due to high spatial resolution and innocuous of the human body at the cost of privacy of human and less standoff distance due to high atmospheric loss[6-7]. The x-ray scanner used to detect concealed weapon but cannot scan human body like luggage because the ionising property of x-rays is harmful to human body[8]. The MMW based imaging technique has been considered diligently for the military, scientific and industrial[9-12].

MMW imaging has been usually categorised into two classes, active and passive type[13-14]. In passive mode, a very high sensitive receiver has been required due to very low received signal intensity, on the other hand, a high signal-to-noise ratio has been acquired with the help of the active imaging system. The image acquired using the active MMW imaging system may become inaccurate by glint and speckle due to coherent illumination[15]. The recognition rate can be improved with various signal processing steps. To improve the quality of images, several researchers have demonstrated various signal processing steps like frequency domain processing, spatial filtering, intensity transformation, image restoration and image segmentation at microwave frequency range for hidden target identification[16-21]. However, these techniques need to critically analyse for fully utilisation in MMW images for concealed target identification. Very limited work on the basis of signal processing method has been reported at 60 GHz and more than 60 GHz frequency for complete concealed target detection and identification[22-26].

The dielectric contrast among matchbox, gun, and knife (with a wooden handle) are quite large i.e., matchbox has a very low dielectric constant so it is challenging to detect high dielectric and low dielectric targets from same image

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processing techniques. Therefore attempt has been made with the help of ANN-based algorithm for detection of such types of the concealed targets.

2. MMW MEASUREMENT SET UP AND TARGET ARRANGEMENT

2.1 MMW Experimental Setup

Active MMW imaging system has been arranged using the vector network analyser (VNA), pyramidal horn antenna and VNA cable[21]. Target has been placed on the movable wooden frame in front of the fixed antenna. The movable frame with the target is moved in vertical as well as horizontal direction at 2 cm step size[9]. The active MMW imaging system has been used in stepped frequency continuous wave mode (SFCW).

The MMW system received the reflected signal in the frequency dominion at N = 201 frequency point. The number of frequency points (N) and the bandwidth of SFCW radar decides unambiguous range and down range resolution respectively[27]. Cross range depends on the center frequency of the transmitted signal and provides the ability to distinguish two closely separated targets in the lateral direction[22]. In our experiments, cross range resolutions is $\Delta y = \frac{\lambda R}{D} = 1.17$ cm cm at a distance of 75 cm. Where Δy is the cross-range resolution, $R$is the distance of the target from antenna, λ =0.5 cm (60 GHz) is the wavelength and D = 2 cm x 16 = 32 cm is the lateral dimension of synthetic aperture. Three different types of weapons like, metal foil wrapped toy gun, stainless steel knife with a wooden handle and paper board match box have been taken as shown in Fig. 1. Target is placed on the polystyrene sheet which has approximately 2 cm thickness. The permittivity of the human body is approximately similar as polystyrene sheet at 60 GHz[28]. The reflection coefficient (S11) has been also plotted for human body and polystyrene sheet as shown in Fig. 2 and observed that the reflection coefficient of the polystyrene is approximately equivalent as the human body for frequency range 59 GHz to 61 GHz.

2.2 Data Acquisition

Targets have been scanned by moving a wooden frame in lateral as well as vertical directions to get complete imaging information. The data has been assembled using A-scan, B-scan, and C-scan techniques[9]. A-scan indicates only absence or presence of the target in downrange direction. B-scan, which is an assembly of several A-scan in the lateral direction, delivers the information about the width of the target. C-scan, which is an assembly of various B-scan in the vertical direction,

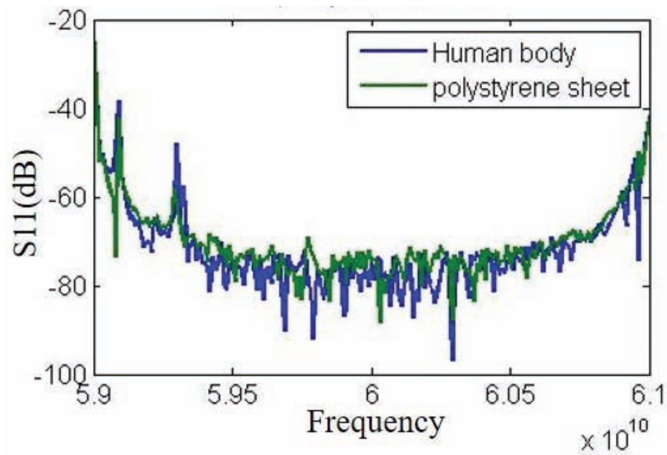


Figure 2. Reflection Coefficient for human body and polystyrene sheet.

gives complete knowledge about the shape of the target in terms of height and width. The C-scan, which is a 3D matrix, provides intensity values of the scattered signal in the direction of downrange, horizontal and vertical. The whole C-scan data is as follows

$$\text{C-scan} = (\text{Scattered data})_{NxMxP} \tag{1}$$

where N = 201 is the number of frequency steps, M = 16 is lateral scanning points, and P = 21 is a number of vertical scanning points. Total one hundred fifty C-scan data have been taken, seventy-two for each combination of targets either covered with cotton or woolen fabric and six for empty targets in which first one hundred thirty-five sets of data were used for development of the algorithm and rest fifteen were used for validation purpose.

3. PRE-PROCESSING STEPS

SFCW radar collects the complex reflection coefficient (S11) from the target in terms of magnitude and phase at each stepped frequency[29]. Pre-processing mainly consists of three steps such as frequency domain to time domain transformation, the time domain to spatial domain transformation and reference calibration with metal sheet after collecting A-scan data to obtain the target's exact location in the down range. A-scan provides a matrix whose dimension is 201x1. The range resolution of the MMW system is $\Delta x = \frac{C}{2N\Delta f} = 7.5$ cm at 2 GHz bandwidth.

MMW radar system must be calibrated to remove systematic errors due to uneven frequency response, VNA cables and antenna. This systematic error adds some delay in

(a) (b) (c) (d) (e)

Figure 1. Target used for concealed weapon detection with MMW imaging system (a-c) targets without covering cloth, (d) and (e) concealed targets covered with cotton and woolen fabric piece, respectively.

the received signal, which dislocates the actual target position in the downrange direction. Hence, a reference calibration is executed by insertion a large metal sheet near the antenna and the obtained distance is subtracted from the A-scan data to achieve the true target position in the downrange direction[30]. This provides the exact target location i.e. 0.75 m as shown in Fig. 3. The target position is determined by taking the standard deviation of each range bin image. The range bin, which contains the target image, has a maximum variation in data due to different dielectric targets as shown in Fig. 4. Therefore, the position of maximum peaks of standard deviation has been found. It gives the target position at particular range bin index which is a 10th range bin position as shown in Fig. 4. Hence, the 3-D C scan matrix has converted into the 2-D matrix by taking a slice at 10th range bin index to obtain the complete shape of targets in terms of height and width, called raw image. Fig. 5 shows raw C scan images, but these images are not very clear to identify targets due to noise and missed out pixel point during scanning of targets. Therefore, need to develop such as algorithm which is able to detect the shape of concealed objects beneath the different cloth.

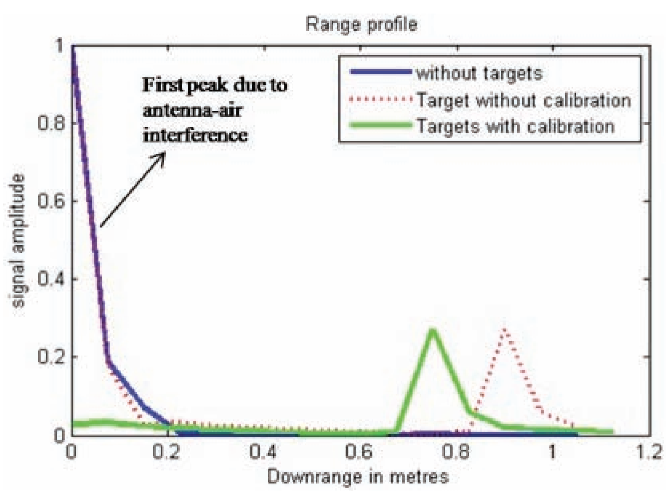


Figure 3. Range profile of concealed target.

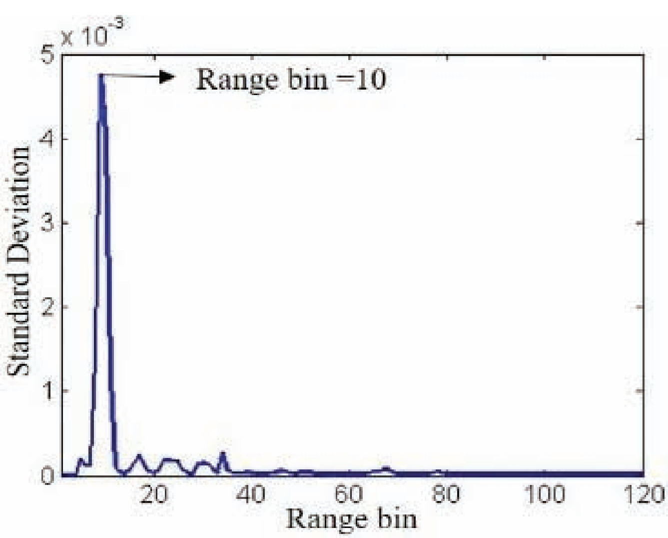


Figure 4. Standard deviation of each range bin.

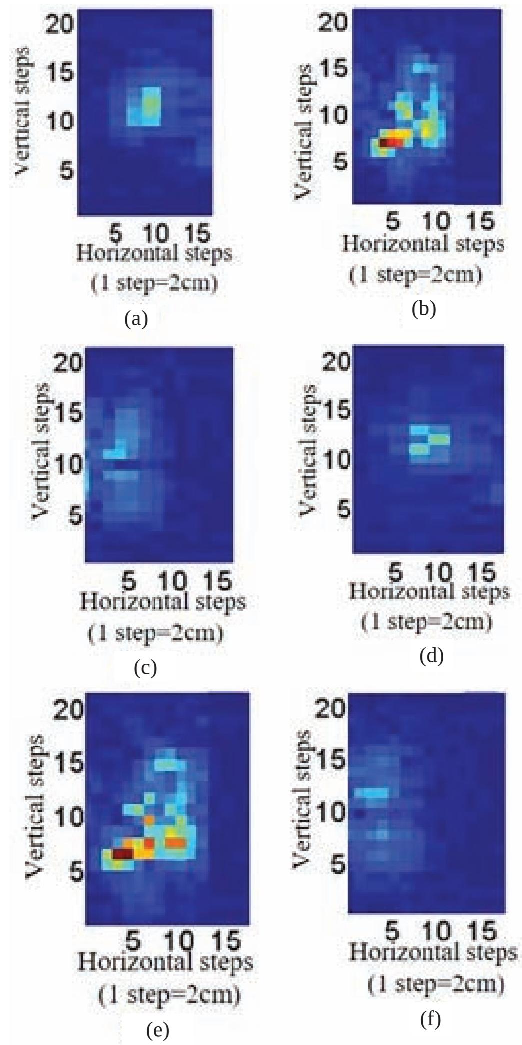


Figure 5. Raw C-scan image for a concealed (a-c) matchbox, gun, and a knife under cotton cloth respectively (d), (e), and (f) matchbox, gun, and a knife under woolen cloth, respectively.

One of the major problems to detect the shape of the targets is the orientation of weapons. It is almost impossible to have the targets in either vertical or horizontal position during scanning of the targets. If it is tried to find the rotated shape target then it will create a problem owing to the lower resolution of the MMW system. Hence, the ANN-based procedure has been used to detect the concealed targets at any shape, size, and orientation.

4. TARGET DETECTION USING ARTIFICIAL NEURAL NETWORK

The target is not able to identify the particular shape with slight coordination effect as shown in Fig. 6, which shows the raw image under the woolen cloth at rotation angle 60°. Our prime task is to detect the concealed targets at different angle under the cloth. To resolve such problem, three targets such as a gun, knife, and matchbox of two different sizes have been taken and rotated between 0° to 360° at every 30° under two dissimilar covering cloths such as woolen and cotton. Hence, the data set of 150 samples are made with twelve dissimilar

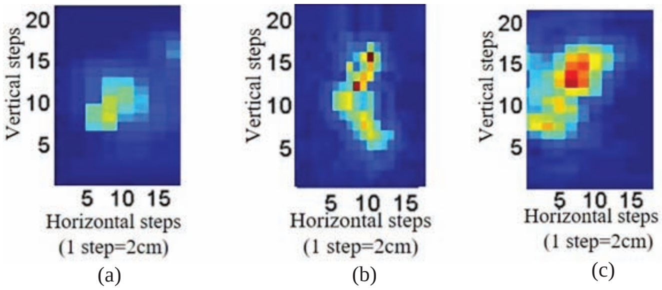


Figure 6. 2D C-scan raw image under woolen cloth at 60° rotation (a) Matchbox (b) Gun and (c) Knife.

rotation directions (0° to 360°) for the three targets under two dissimilar covering cloth and six without target readings have been taken under woolen and cotton fabric (12x6x2+6=150). In consideration of target identification, 135 randomly data (90 per cent) out of entire 150 samples data have been selected to train ANN model and for testing and validation point of view of the trained neural network, the remaining 15 data (10 per cent) has been considered. To recognition the image, a multi-layer feed-forward neural network (MFFNN) is used which consists of the pattern recognition network with a sigmoid transfer function and scaled conjugate gradient (SCG) training function in both output layer and hidden layer[31]. The SCG training function has been used for supervised learning algorithm which has the faster convergence rate than any other training functions like back propagation and gradient descent with momentum due to step size scaling mechanism, and no line search per learning iteration[32]. The weight and bias value of hidden layer has been updated according to SCG function and output of the network, which should be valued between 0 to 1, has been constrained by a sigmoid transfer function. The mean squared error (MSE) criterion is used for learning algorithms to train the neural network, which is defined as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(r_i - n_i)^2 \tag{2}$$

where n is the network output image, r is the target image and N is a total number of pixels. The neural network first produces its own output vector r according to input vector and try to match with target vector n. If MSE is in a predefined range, i.e. below 0.01 for optimum performance, then no further learning takes place, otherwise, the weights between input and the hidden layer and the hidden layer to output layer are adjusted to reduce MSE. Better performance of the neural network can be achieved by the lower value of *MSE*.

The complete flow chart for the generation of *NN* model for a rotation invariant target's image reconstruction is shown in Fig. 7.

The following layer is used to configure the neural network

- Input layer: Pixel intensity points of every raw image, which is a 2-D matrix (21x16 = 336), is changed into column matrix (336x1). Therefore, for 135 different images, the dimension of the input matrix is (336x135), which is used to train the neural network, as shown in Fig. 8.
- Hidden Layer: The stability of NN model and the error at output nodes is highly influenced by the middle layer (Hidden layer) of the neural network. The hidden layer of the proposed NN model consists 50 neurons. Here, numbers of neurons are iteratively chosen on the basis of trial and error by keeping the balance between minimising

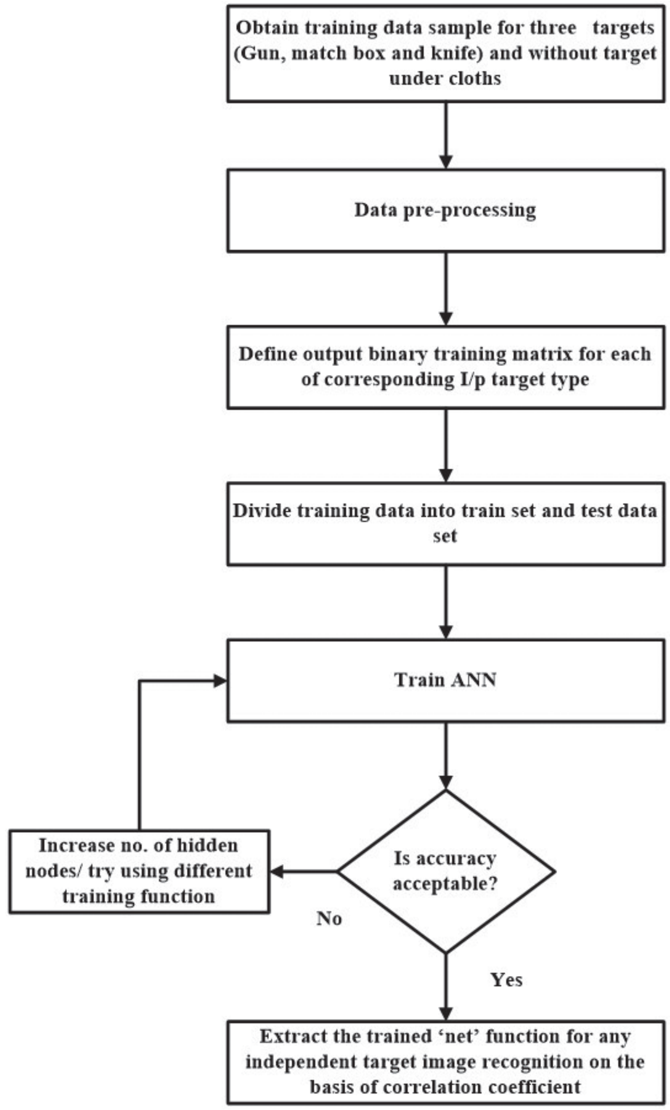


Figure 7. Flow chart describing the generation of rotation and size invariant NN model.

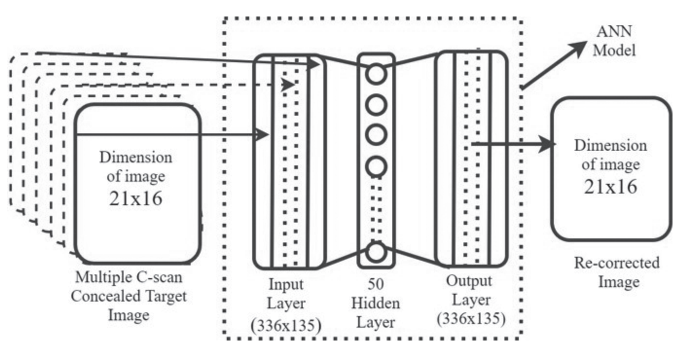
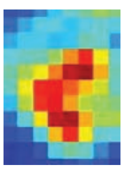
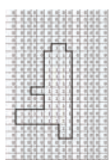
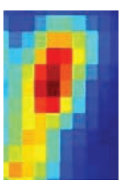
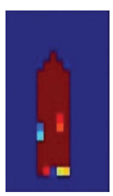
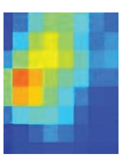
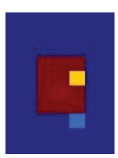
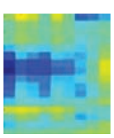
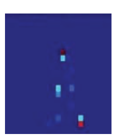


Figure 8. The arrangement of scale and rotation invariant NN model for the target's image re-correction.

the output error as well as ANN system complexity[33].

- Output layer: The image recognition approach has been used to reconstruct the correct target's shape instead of pattern classification labels to differentiate the shape. To recognize the shape of the target, the output matrix for training the neural network is produced according to the shape of the input target that is in binary form (0,1) as shown in Table 1 column c. three different shapes of considered targets have been taken and the corresponding different binary matrix has been assigned for training the neural network. For example, two different sizes of matchbox have been taken and assign two different corresponding sizes of the binary matrix. Now, these considered targets, under woolen and cotton cloth, have been rotated at 30° from 0° to 360° to generate 144 different samples and for every rotation, the equivalent binary matrix has been allocated as the corresponding shape and size of the target. Therefore, the output matrix has been generated with the help of the raw input matrix and the corresponding binary matrix form as shown in Table 1 column d after training the neural network.

Table 1. Results of the proposed trained neural network using independent data sets.

Target description	Test targets	Binary training matrix	Output image	Mean square error (MSE)
(a)	(b)	(c)	(d)	(e)
Rotated Gun under wollen cloth at 45°				0.0092
Rotated Knife under cotton cloth at 30°				0.0056
Rotated Match box under wollen cloth at 60°				0.0027
No target under wollen cloth				0.0012

The main problem of ANN is that it has not self-learning ability like a human neural network. The neural network has been trained for three different types of input and one background scene. Whatever the input is applied, the generated output will be according to the target input data. Therefore, to remove such type of problem, the signature of targets has been generated according to, firstly, the summation of rows and followed by a summation of columns of raw image as shown in Figs. 9, 10 and 11. Whatever the input has been applied for validation, first the correlation coefficient ($r_{X,Y}$) has been calculated between the previous generated Figs. (9, 10 and 11) and signature of the validation data according to Eqns (3 and 4). If the correlation coefficient is above the 85 per cent, then the new data is used for validation purpose.

$$COV(X,Y) = S_{X,Y} = \sum_{i=1}^{N} \frac{(X_i - X_{mean})*(Y_i - Y_{mean})}{N-1} \quad (3)$$

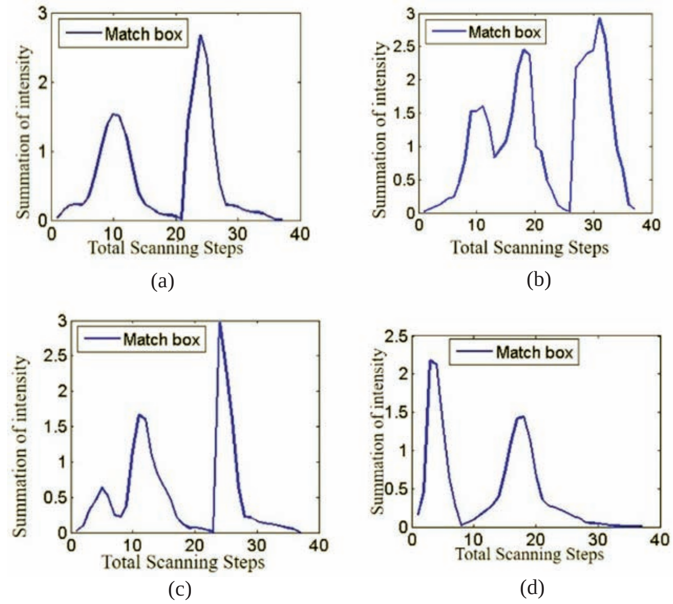


Figure 9. The signature of a matchbox under woolen cloth at (a) 0° orientation (b) 30° orientation (c) 60° orientation and (d) 90° orientation.

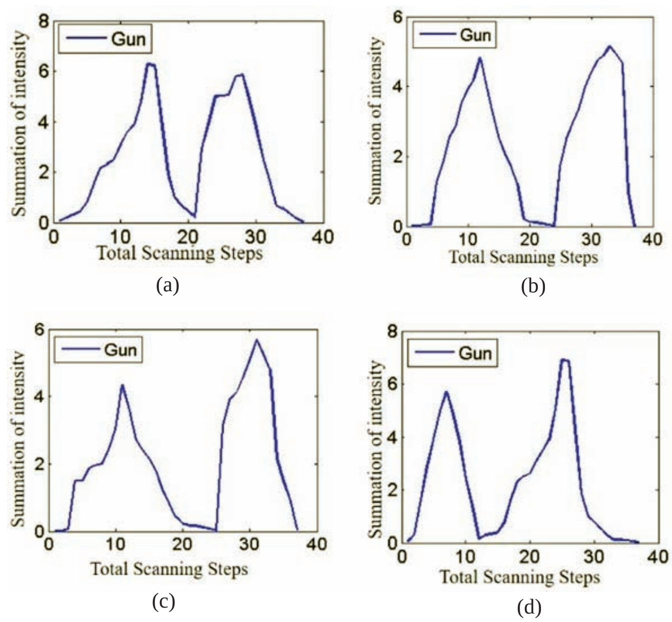


Figure 10. The signature of a gun under woolen cloth at (a) 0° orientation (b) 30° orientation (c) 60° orientation and (d) 90° orientation.

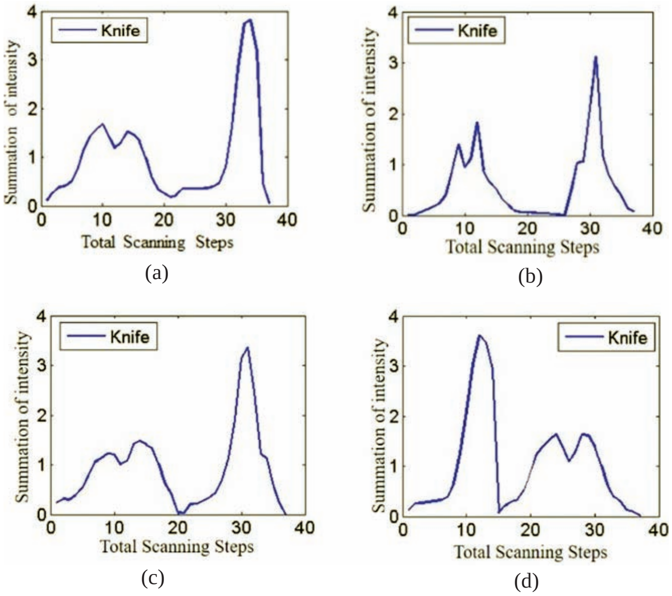


Figure 11. The signature of a knife under woolen cloth at (a) 0° orientation (b) 30° orientation (c) 60° orientation and (d) 90° orientation.

$$r_{X,Y}(\%) = \frac{S_{X,Y}}{S_x S_Y} \tag{4}$$

where N is the number of samples, $S_{X,Y}$, S_X and S_Y is the covariance between the previous generated sample and validation sample, standard deviation of the previous sample and standard deviation of the validation sample, respectively.

5. VALIDATION OF THE DEVELOPED ANN MODEL

The performance of ANN model is tested through fifteen autonomous data samples for a real-world demonstration that is not used to train the ANN model. First, the signature of validated data has been drawn as shown in Fig. 12. The correlation coefficient values have been calculated between all previously generated signature and the validation signature. The correlation coefficient values are above 90 per cent between Fig. 12(a) and Fig. 10 and for Fig. 12 (a) and Figs. (9, 11), its values are less than 70 per cent. The maximum correlation coefficient value has been obtained from Fig. 12(a) and Fig. 10(c) i.e. 96.23 per cent. It means that the validation data is very similar to the gun data. The same type of analysis has been done to validation data from a matchbox and obtained correlation coefficient values above 87 per cent for Fig. 12 (b) and Fig. (9). Now the trained ANN has been validated for independent data sets and obtained a corresponding binary image as shown in Table 2, which is also shown the mean square error (MSE) between NN output image and desired image. As shown in Table 2, rotated gun and a matchbox images are recognised with the true size and shape as a correct gun and a matchbox output images, with MSE of 0.0065, 0.0034, respectively. Thus, the proposed neural network algorithm has the capability to correctly recognize the considered target at any shape, size, and orientation.

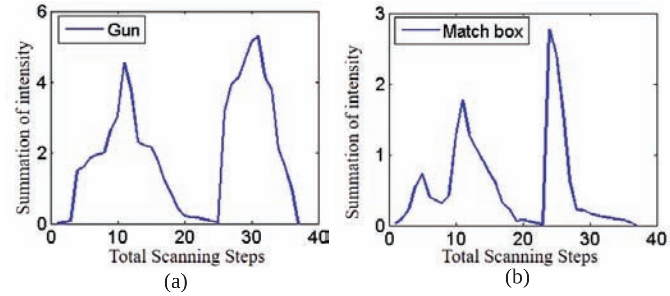
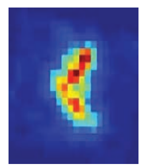
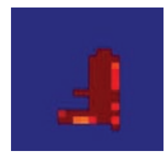
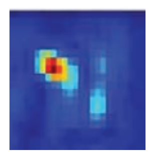
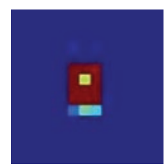


Figure 12. The signature of (a) A gun under cotton cloth at 60° orientation and (b) A matchbox at 300° orientation.

Table 2. The results of the proposed trained NN model with an independent set of test data for gun and matchbox

Target description	Test targets	Output image	Mean square error (MSE) for ANN
(a)	(b)	(c)	(d)
Rotated Gun under wollen cloth at 60°			0.0065
Rotated Match box under wollen cloth at 300°			0.0034

6. CONCLUSION

In this paper, an active MMW SFCW radar imaging system has been designed for concealed target detection for security applications. C scan methodology was used for complete target's data acquisition. The metal sheet calibration technique has been used to remove the delay added by VNA cable and antenna for finding the actual position of the target. The target position is determined by taking the standard deviation of each range bin image. ANN technique with the conjunction of correlation coefficient has been used to make an image at any shape and orientation. After the development of the algorithm, authors have been successfully tested on the various combination of concealed weapons at a different angle under various cloths and got the almost same shape of the image as concealed weapons.

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Over concealed weapon detection with MMW radar system activity headed by the author and under his supervision and guidance concealed weapon detection with MMW radar system has been carried out.