CHAPTER 5

APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR RECOGNITION OF TARGET*

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5.1 Introduction

The obtained target image does not correspond to the actual shape and size of targets. Also the radar images show very little resemblance to optical images due to which it becomes difficult to interpret from imaged scene. Therefore, there is need of methodology for analysis of radar images which can automatically perform recognition task and thereby help in decision making. To identify the target, a robust feature that gives description of target is required. A robust feature should have resolution-independent or target position-invariant, orientation and size invariance property. Many authors have contributed in the direction of classification of target behind a wall using different techniques. Previous work on target classification in through wall imaging, includes the use of the principal component analysis on two-dimension imaging (range vs crossrange) [Mobasseri and Rosenbaum (2008)] and superquadric fitting [Debes *et al.* (2010b)] on segmented objects on three-dimensional imaging. Both approaches, however, provide features that are not system resolution-independent or target position-invariant. This corresponds to the implicit assumption of imaging in the far field, which is not appropriate for most indoor imaging scenarios. In previous reported articles, identification of target in TWI are achieved with the use of high range resolution profile (HRRP) based feature on segmented three-dimensional through-the-wall images of target [Smith and Mobasseri (2011)]. As noted in their papers, although they obtained good quality of results in same orientation but the proposed framework has not been modeled explicitly for orientation of target. Thus, it will assign separate feature for different orientations of the same target rather than having a single feature that covers all orientations. This will make the process complex and computationally intensive. Another more promising technique for identifying target is to estimate of shape of target [Hantscher *et al.* (2006)]. So, our main focus here is laid on a shape recognition of hidden objects which is also of great interest in many non-invasive sensing applications. Various authors have proposed methodology for shape estimation of target behind a wall. In the previous reported articles, shape of target have been estimated with use of the Inverse Boundary Scattering Transform (IBST) on B-scan data [Hantscher *et al.* (2006)], and envelope of modified sphere on C-scan data [Kidera *et al.* (2009)]. With these methods quite accurate shape of target has been achieved however these methods often need complex preprocessing, like, the IBST where wavefronts need to be recognized and estimated and the enveloped of modified sphere where the curvature of target shape have to estimated [Mirbach and Menzel (2011)]. Recent developments have achieved even higher accuracy but with a significant increase in complexity and computational time [Mirbach and Menzel (2011), Wu *et al.* (2013), Dehmollian (2010)].

In this chapter, a methodology for shape and size recognition of the target from through-the-wall radar images is described. This methodology is less complex and easy to implement. The proposed methodology can recognize shape of target irrespective of its variation in orientation and size. For complete identification (i. e., shape and size) of targets very limited work has been reported so far. Therefore, to recognize and visualize the actual shape and size of target behind a wall, a novel methodology using ANN is proposed in this chapter. The present ANN model can reconstruct the actual target shape nullifying any rotation or size variations for the considered regular shapes. Thus, it would enable us to improve the quality of through-the-wall images.

5.2 Methodology

The developed methodology consists of data acquisition, average subtraction, 2D C-scan through-the-wall image formation, image enhancement, segmentation and shape and size identification using neural network. Flowchart of different steps applied is shown in Figure 5.1 and the detail of each step is discussed below.

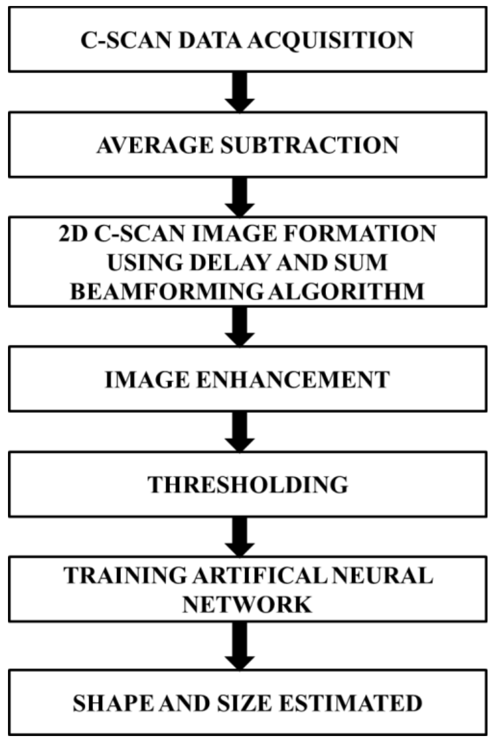


Figure 5.1. Flowchart of methodology for recognition of target shape and size.

5.2.1 Data acquisition

For the development of model for shape and size recognition of the target, an experiment has been carried out. C-scan data is measured using measurement set-up shown in Chapter 2 for different shapes and sizes of wooden and metallic targets. The details about list of the target used for the purpose of target recognition is given in Table 5.1.

5.2.2 Average Subtraction

The received signal contains reflected target as wells undesired signals due to reflection from antenna mismatch, and background noise. To remove these undesired signals, average subtraction is performed using equation (4.1), as discussed in Chapter 4. For this purpose, mean vector of each B-scan is calculated and further subtracted from its each individual A-scan.

Table 5.1 Details about list of target samples considered.

S. No.	Shape	Target I/D	Size	Orientation	Material	Generated Image
1.	Triangle	WTR1	35cmX35cmX35cm	0	Wood	Real
2.	Triangle	WTR2	35cmX35cmX35cm	45	Wood	Real
3.	Triangle	WTR3	35cmX35cmX35cm	135	Wood	Real
4.	Triangle	MTR1	35cmX35cmX35cm	0	Metal	Real
5.	Triangle	MTR2	35cmX35cmX35cm	45	Metal	Real
6.	Triangle	MTR3	35cmX35cmX35cm	135	Metal	Real
7.	Square	WSR1	30cmX30cm	0	Wood	Real
8.	Square	WSR2	30cmX30cm	45	Wood	Real
9.	Square	WSR3	30cmX30cm	135	Wood	Real
10.	Square	MSR1	30cmX30cm	0	Metal	Real
11.	Square	MSR2	30cmX30cm	45	Metal	Real
12.	Square	MSR3	30cmX30cm	135	Metal	Real
13.	Rectangle	WRR1	50cmX30cm	0	Wood	Real
14.	Rectangle	WRR2	50cmX30cm	45	Wood	Real
15.	Rectangle	WRR3	50cmX30cm	135	Wood	Real
16.	Rectangle	MRR1	50cmX30cm	0	Metal	Real
17.	Rectangle	MRR2	50cmX30cm	45	Metal	Real
18.	Rectangle	MRR3	50cmX30cm	135	Metal	Real

5.2.3 Image Formation

After performing average subtraction on acquired C-scan data, delay and sum beam forming algorithm is applied on C-scan data to form the through-the-wall radar images as discussed in Chapter 4. Then, the two dimensional image of target (horizontal cross range vertical cross range) is plotted by considering a XY plane at fixed target range bin ($z = z_{target}$) which is selected by observing range profile. Thus, a virtual image of size 50X50 pixels is formed.

Figs. 5.2 (a-d) show the 2D C-Scan through-the-wall radar image (cross-range vs height) of metallic rectangular (Target id-MRR1), metallic square (Target id-MSR1), wooden rectangle (Target id-WRR1), and wooden square (Target id-WSR1), target at 0^0 orientation, respectively. Detail description about target is shown in Table 5.1. These 2D through-the-wall radar image provides useful information of target extent in terms of length and height. Once optimal image processing methods are applied to these 2D through-the-wall radar image (cross-range vs height) one can extract valuable information about target shape and size (i.e. length and height). The 2D C-scan through-the-wall radar image will be further processed for purpose of target recognition.

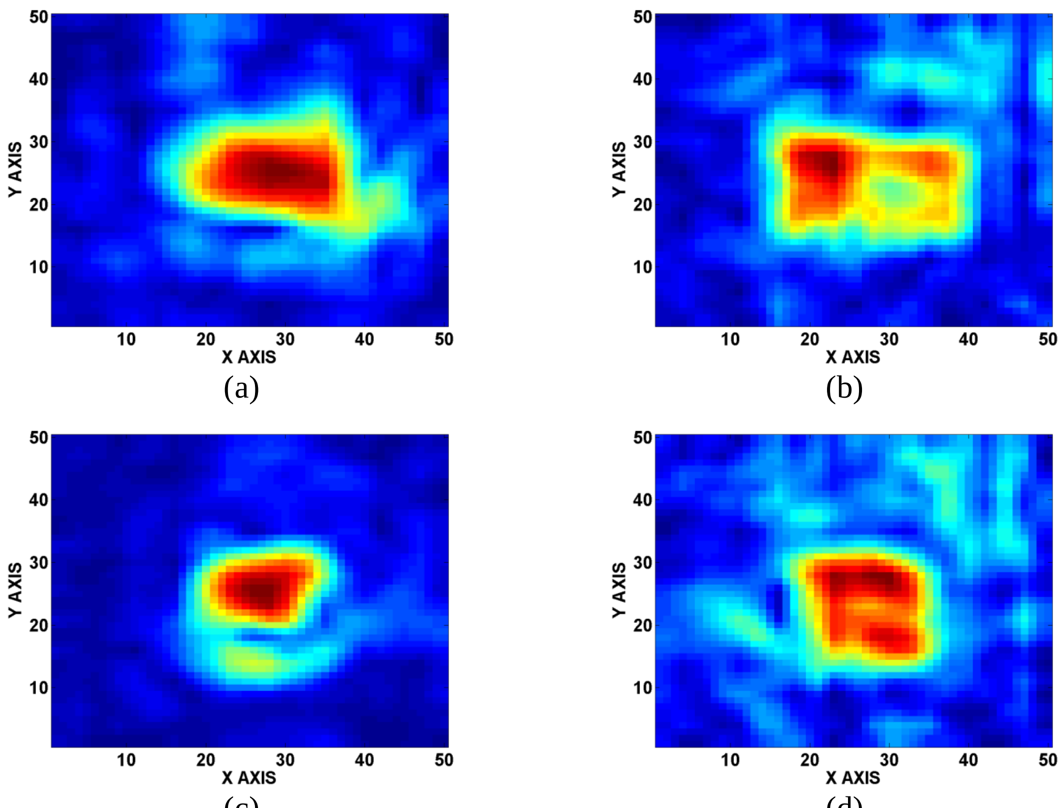


Figure 5.2. 2D C-Scan through-the-wall radar image obtained using delay and sum beamforming method on imaging plane along X and Y axis of target id **(a)** MRR1, **(b)** WRR1, **(c)** MSR1and **(d)** WSR1.

5.2.4 Image Enhancement

The 2D C-scan through-the-wall radar image contains unwanted pixels, other than desired target pixels, due to background noise, multipath reflection and other factors. Therefore, for enhancement of target pixels various image enhancement methods such as weiner filter, adaptive median filter, mean filter and spatial maximum filter are considered. Performance of weiner filter, adaptive median filter, mean filter and spatial maximum filter are examined [Gonzalez *et al.* (2007)], and are compared on the basis of PSNR as shown in Table 5.2. PSNR is calculated from normalized 2D C-scan through-the-wall radar image and spatial filtered image using equations (5.1) and (5.2) [Verma *et al.* (2009)]

$$MSE = \frac{1}{UXV}\sum_{i=1}^{V}\sum_{j=1}^{U}\left(\mathrm{G(i,j)} - I\mathrm{(i,j)}\right)^2 \tag{5.1}$$

$$PSNR(\mathrm{dB}) = 10\log\left(\frac{1}{MSE}\right) \tag{5.2}$$

where I represent a 2D C-scan through-the-wall radar image, G represent a 2D C-Scan through-the-wall radar after applying spatial filtering, U represents no of pixels in row, and V represents number of pixels in the columns. The image enhancement has been done using discrete convolution. In filtering operation, the pixels of an image are modified by moving the filter mask of size 3X3 from one pixel point to another pixel point of image.

Table 5.2. PSNR (dB) value of enhanced 2D C-scan through-the-wall radar image of targets MRR1, WRR1, MSR1, WSR1 after applying various spatial filtering techniques

Filtering method	MRR1	WRR1	MSR1	WSR1
Spatial max	24.89	24.75	25.15	24.04
Mean	37.26	33.86	39.05	33.56
Weiner	40.68	37.28	41.9	36.56
Adaptive median	51	44.47	47.22	42.07

After comparing the PSNR of all filtered images, it has been found that adaptive median filter provides good results in comparison with the other filtering operations. Therefore, for enhancement of target pixels adaptive median filter is considered. Figures 5.3 (a-d) shows the enhanced 2D C-scan through-the-wall radar image of targets MRR1, WRR1, MSR1, WSR1. The intensities of target pixels points in these images are significantly enhanced. The adaptive median filter also enhances the boundary of targets. These enhanced image is further used for detection and identification.

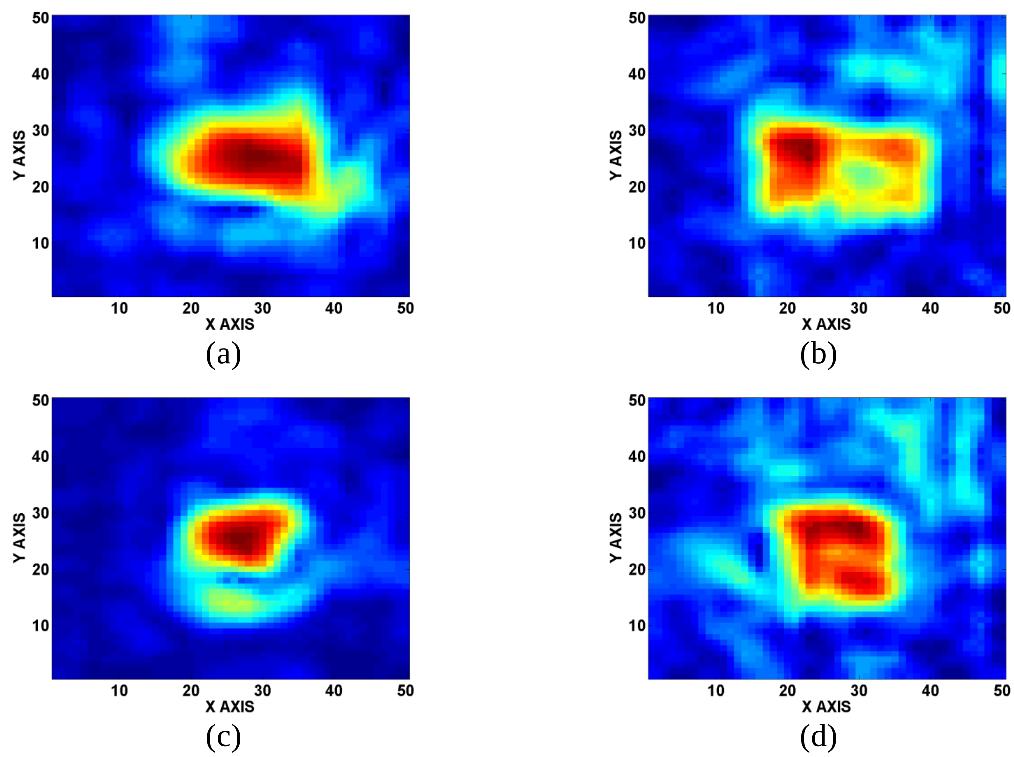


Figure 5.3. Adaptive median filtered image for target id **(a)** MRR1, **(b)** WRR1, **(c)** MSR1, and **(d)** WSR1.

5.2.5 Statistic Based Thresholding Technique

The statistics value of image plays a very important role to determine the boundary of targets. Therefore, statistics based thresholding technique is applied to determine the shape of targets. The threshold is calculated according to equation (5.3) which is given as

$$T = mean(\mu) + n \times standard\ deviation(\sigma) \tag{5.3}$$

The “n” is called scaling parameter. The value of “n” has been determined by solving a nonlinear optimization problem using genetic algorithm as discussed in Chapter 4. Using the thresholded binary image, the 2D C-Scan through-the-wall radar image is masked, producing 2D C-Scan through-the-wall radar image with the target region only. The segmented image of metallic rectangular is shown in Figure 5.4 (a). The shape of targets is not as clear as it should be due to few undesired pixel points have been observed in images after thresholding techniques. Now the ANN technique has been proposed to detect the actual shape of targets.

5.2.6 Target Shape Recognition Using Artificial Neural Network

The segmented image of target does not correspond to the actual shape and size of targets. Also the radar images show very little resemblance to optical images due to which it becomes difficult to interpret from imaged scene. Therefore, this segmented image of target using delay and sum imaging algorithm is further processed using artificial neural network (ANN) to predict actual shape and size of target. One of the major problems which occur in recognizing the shape of the targets is with its orientation. It is difficult to identify the particular shape of the target with a slight orientation effect. Thus, in order to make model orientation and size invariant a lot of 2D C-scan through-the-wall radar images of the target is required to train the ANN to increase the detection accuracy of the ANN model. The number of data can be increased with the help of multiple scanning of various targets behind the wall but it requires a long time. Therefore to save time, C-scan data have been collected for the metallic and wooden target of different shapes and orientation to generate the 2D C-Scan through-the-wall radar image and then synthetic data of 2D C-Scan through-the-wall radar image of different sizes of targets is generated using morphological technique. Morphology is a tool that has been used for extracting image components that are useful in the representation and description of region shape, such as boundaries, skeletons and convex hull. Dilation and erosion are two operations that are fundamental to morphological filtering [Gonzalez *et al.* (2007)]. Dilation and erosion are an operation that grows and compress or thickens and thin objects in a binary image, respectively. The 'structuring element' controls the specific manner and extent or reduces of the image. Structuring elements are typically represented by a matrix of 1s and 0s. Mathematically, dilation and erosion can be defined in terms of set operations as [Gonzalez *et al.* (2007)]:

$$A \oplus B = \{z \mid (\hat{B})_Z \cap A \neq \phi\} \tag{5.4}$$

where A is thresholded image, B is the structuring element and ϕ is the empty set. The structuring element B = [1 1 1] increases and decreases the horizontal depth of image, the structuring element B = [1; 1; 1] increases and decreases the vertical depth of image and the structuring element B = [0 1 0; 1 1 1; 0 1 0] increases and decreases the vertical as well as horizontal depth of image by using dilation and erosion techniques, respectively. For example, 2D C-Scan through-the-wall radar image of metallic and wooden rectangular targets of size (50cm X 30cm) at orientation 0^0, 45^0 and 135^0 is generated by real scanning of target and synthetic 2D C-Scan through-the-wall radar image of metallic and wooden rectangular target of size (45cm X 25cm), (55cm X 35cm), (60cm X 40cm) and (65cm X 45cm) at orientation 0^0, 45^0, and 135^0 is generated by performing morphological dilation and erosion operation with structuring matrix [0 1 0; 1 1 1; 0 1 0], respectively. Similarly, 2D C-Scan through-the-wall radar image of metallic and wooden square targets of size (30cm X 30cm) at orientation 0^0, 45^0 and 135^0 has been generated by real scanning of target and synthetic 2D C-scan image of metallic and wooden square target of size (35cm X 35cm), (40cm X 40cm), (45cm X 45cm) and (50cm X 50cm) at orientation 0^0, 45^0, and 135^0 is generated by performing morphological dilation operation with structuring matrix [0 1 0; 1 1 1; 0 1 0], respectively. Also, 2D C-Scan through-the-wall radar image of metallic and wooden triangle targets of size (35cm X 35cm X 35cm) at orientation 0^0, 45^0 and 135^0 is generated by real scanning of target and synthetic 2D C-scan through-the-wall radar image of metallic and wooden triangle target of size (30cm X 30cm X 30cm), (40cm X 40cm X 40cm), (45cm X 45cm X 45cm) and (50cm X 50cm X 50cm) at orientation 0^0, 45^0, and 135^0 is generated by performing morphological dilation and erosion operation with structuring matrix [0 1 0; 1 1 1; 0 1 0], respectively. The dilation technique extends the size of image by 5 cm because one pixel size of image is (2.5 cm X 2.5 cm) and erosion technique reduces the size of image by same step. Figures 5.4(a-d) show the 2D C-Scan through-the-wall radar image of metal rectangular target of size (50cm X 30cm) at orientation 0^0 has been generated by real scanning of target and synthetic 2D C-Scan through-the-wall radar image metal rectangular target of size (45cm X 25cm), (55cm X 35cm) and (60cm X 40cm) have been generated by performing morphological dilation operation with structuring matrix [0 1 0; 1 1 1; 0 1 0], respectively. Here A is a thresholded image, B is the structuring element and φ is the empty set. Thus, 18 samples of 2D through-the-wall radar image of size 50 X 50 are captured by through-the-wall radar imaging system and the remaining 72 samples are generated by morphological technique as shown in Table 5.3. Thus total 90 samples of data are used to train the neural network.

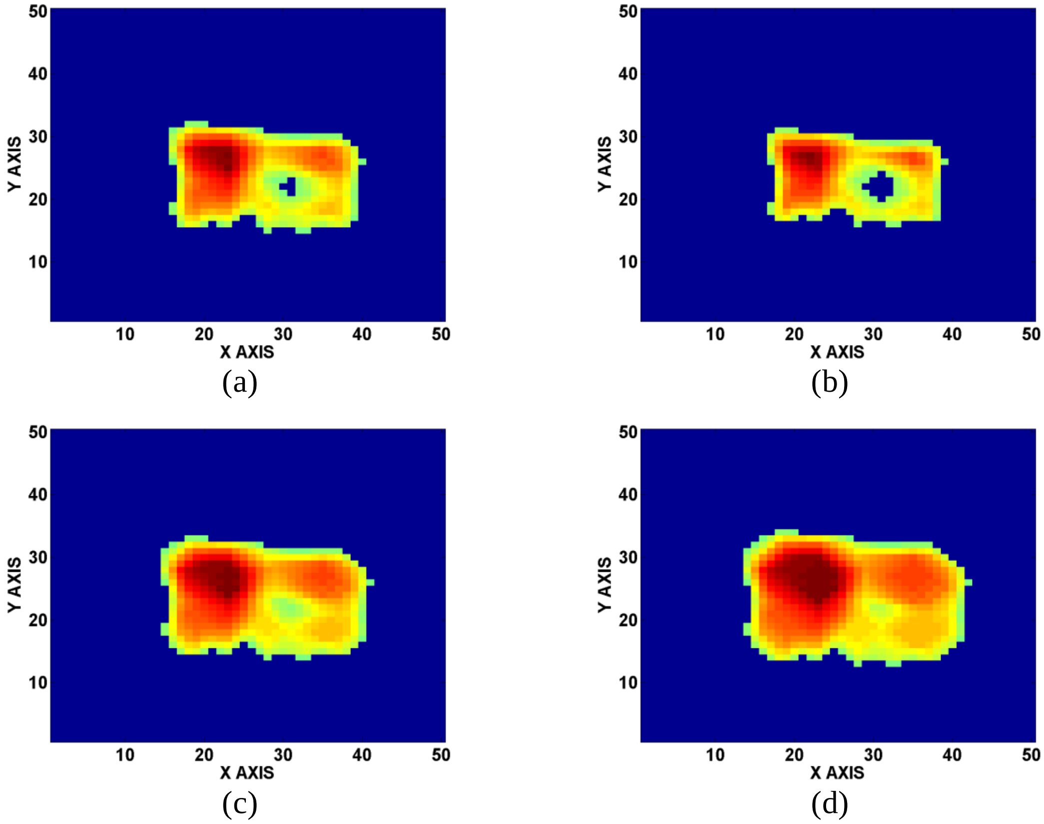


Figure 5.4. (a) Statistics based thresholded 2D C-Scan through-the-wall radar image of actual rectangular metal target of size 50cm X 30cm. **(b)** Horizontally and vertically shrinked 2D C-Scan through-the-wall radar image of rectangular metal target of size 25cm X 45cm obtained after applying morphological erosion technique on statics based thresholded 2D C-Scan through-the-wall radar image of actual rectangular metal target of size 50cm X 30cm. **(c)** Horizontally and vertically expanded 2D C-Scan through-the-wall radar image of rectangular metal target of size 55cm X 35cm obtained after applying morphological dilation technique on statics based thresholded 2D C-Scan through-the-wall radar image of actual rectangular metal target of size 50cm X 30cm. **(d)** Horizontally and vertically expanded 2D C-Scan through-the-wall radar image of rectangular metal target of size 60cm X 40cm obtained after applying morphological dilation technique on statics based thresholded 2D C-Scan through-the-wall radar image of actual rectangular metal target of size 50cm X 30cm.

Table 5.3. List of target samples used for purpose of training and validation of neural network.

S. No.	Shape	Target I/D	Size	Orientation	Material	Generated Image
1.	Triangle	WTR1	35cmX35cmX35cm	0	Wood	Real
2.	Triangle	WTR2	35cmX35cmX35cm	45	Wood	Real

3.	Triangle	WTR3	35cm X35cmX35cm	135	Wood	Real
4.	Triangle	WTV4	30cmX30cmX30cm	0	Wood	Virtual
5.	Triangle	WTV5	30cmX30cmX30cm	45	Wood	Virtual
6.	Triangle	WTV6	30cmX30cmX30cm	135	Wood	Virtual
7.	Triangle	WTV7	40cmX40cmX40cm	0	Wood	Virtual
8.	Triangle	WTV8	40cmX40cmX40cm	45	Wood	Virtual
9.	Triangle	WTV9	40cmX 40cmX40cm	135	Wood	Virtual
10.	Triangle	WTV10	45cmX45cmX45cm	0	Wood	Virtual
11.	Triangle	WTV11	45cmX45cmX45cm	45	Wood	Virtual
12.	Triangle	WTV12	45cmX45cmX45cm	135	Wood	Virtual
13.	Triangle	WTV13	50cmX50cmX50cm	0	Wood	Virtual
14.	Triangle	WTV14	50cmX50cmX50cm	45	Wood	Virtual
15.	Triangle	WTV15	50cmX50cmX50cm	135	Wood	Virtual
16.	Triangle	MTR1	35cmX35cmX35cm	0	Metal	Real
17.	Triangle	MTR2	35cmX35cmX35cm	45	Metal	Real
18.	Triangle	MTR3	35cmX35cmX35cm	135	Metal	Real
19.	Triangle	MTV4	30cmX30cmX30cm	0	Metal	Virtual
20.	Triangle	MTV5	30cmX30cmX30cm	45	Metal	Virtual
21.	Triangle	MTV6	30cmX30cmX30cm	135	Metal	Virtual
22.	Triangle	MTV7	40cmX40cmX40cm	0	Metal	Virtual
23.	Triangle	MTV8	40cmX40cmX40cm	45	Metal	Virtual
24.	Triangle	MTV9	40cmX40cmX40cm	135	Metal	Virtual
25.	Triangle	MTV10	45cmX45cmX45cm	0	Metal	Virtual
26.	Triangle	MTV11	45cmX45cmX45cm	45	Metal	Virtual
27.	Triangle	MTV12	45cmX45cmX45cm	135	Metal	Virtual
28.	Triangle	MTV13	50cmX50cmX50cm	0	Metal	Virtual
29.	Triangle	MTV14	50cmX50cmX50cm	45	Metal	Virtual
30.	Triangle	MTV15	50cmX50cmX50cm	135	Metal	Virtual
31.	Square	WSR1	30cmX30cm	0	Wood	Real
32.	Square	WSR2	30cmX30cm	45	Wood	Real
33.	Square	WSR3	30cmX30cm	135	Wood	Real
34.	Square	WSV4	35cmX35cm	0	Wood	Virtual
35.	Square	WSV5	35cmX35cm	45	Wood	Virtual
36.	Square	WSV6	35cmX35cm	135	Wood	Virtual
37.	Square	WSV7	40cmX40cm	0	Wood	Virtual
38.	Square	WSV8	40cmX40cm	45	Wood	Virtual
39.	Square	WSV9	40cmX40cm	135	Wood	Virtual
40.	Square	WSV10	45cmX45cm	0	Wood	Virtual
41.	Square	WSV11	45cmX45cm	45	Wood	Virtual

42.	Square	WSV12	45cmX45cm	135	Wood	Virtual
43.	Square	WSV13	50cmX50cm	0	Wood	Virtual
44.	Square	WSV14	50cmX50cm	45	Wood	Virtual
45.	Square	WSV15	50cmX50cm	135	Wood	Virtual
46.	Square	MSR1	30cmX30cm	0	Metal	Real
47.	Square	MSR2	30cmX30cm	45	Metal	Real
48.	Square	MSR3	30cmX30cm	135	Metal	Real
49.	Square	MSV4	35cmX35cm	0	Metal	Virtual
50.	Square	MSV5	35cmX35cm	45	Metal	Virtual
51.	Square	MSV6	35cmX35cm	135	Metal	Virtual
52.	Square	MSV7	40cmX40cm	0	Metal	Virtual
53.	Square	MSV8	40cmX40cm	45	Metal	Virtual
54.	Square	MSV9	40cmX40cm	135	Metal	Virtual
55.	Square	MSV10	45cmX45cm	0	Metal	Virtual
56.	Square	MSV11	45cmX45cm	45	Metal	Virtual
57.	Square	MSV12	45cmX45cm	135	Metal	Virtual
58.	Square	MSV13	50cmX50cm	0	Metal	Virtual
59.	Square	MSV14	50cmX50cm	45	Metal	Virtual
60.	Square	MSV15	50cmX50cm	135	Metal	Virtual
61.	Rectangle	WRR1	50cmX30cm	0	Wood	Real
62.	Rectangle	WRR2	50cmX30cm	45	Wood	Real
63.	Rectangle	WRR3	50cmX30cm	135	Wood	Real
64.	Rectangle	WRV4	55cmX35cm	0	Wood	Virtual
65.	Rectangle	WRV5	55cmX35cm	45	Wood	Virtual
66.	Rectangle	WRV6	55cmX35cm	135	Wood	Virtual
67.	Rectangle	WRV7	45cmX25cm	0	Wood	Virtual
68.	Rectangle	WRV8	45cmX25cm	45	Wood	Virtual
69.	Rectangle	WRV9	45cmX25cm	135	Wood	Virtual
70.	Rectangle	WRV10	60cmX40cm	0	Wood	Virtual
71.	Rectangle	WRV11	60cmX40cm	45	Wood	Virtual
72.	Rectangle	WRV12	60cmX40cm	135	Wood	Virtual
73.	Rectangle	WRV13	65cmX45cm	0	Wood	Virtual
74.	Rectangle	WRV14	65cmX45cm	45	Wood	Virtual
75.	Rectangle	WRV15	65cmX45cm	135	Wood	Virtual
76.	Rectangle	MRR1	50cmX30cm	0	Metal	Real
77.	Rectangle	MRR2	50cmX30cm	45	Metal	Real
78.	Rectangle	MRR3	50cmX30cm	135	Metal	Real
79.	Rectangle	MRV4	55cmX35cm	0	Metal	Virtual
80.	Rectangle	MRV5	55cmX35cm	45	Metal	Virtual

81.	Rectangle	MRV6	55cmX35cm	135	Metal	Virtual
82.	Rectangle	MRV7	45cmX25cm	0	Metal	Virtual
83.	Rectangle	MRV8	45cmX25cm	45	Metal	Virtual
84.	Rectangle	MRV9	45cmX25cm	135	Metal	Virtual
85.	Rectangle	MRV10	60cmX40cm	0	Metal	Virtual
86.	Rectangle	MRV11	60cmX40cm	45	Metal	Virtual
87.	Rectangle	MRV12	60cmX40cm	135	Metal	Virtual
88.	Rectangle	MRV13	65cmX45cm	0	Metal	Virtual
89.	Rectangle	MRV14	65cmX45cm	45	Metal	Virtual
90.	Rectangle	MRV15	65cmX45cm	135	Metal	Virtual

For training, a multilayer feed forward neural network based for pattern recognition is considered with one hidden and output layer [Haykin (2005)]. For training of neural network, 81 (90%) samples out of total 90 data samples is selected [samples having Sr. nos. 1 to 90 in Table 5.3]. The remaining 9 samples are further used for testing on trained neural network. Among the 81 samples we have randomly selected 70% of samples for training and remaining 30% for validation, and testing point of view in a ratio of 15% and 15%, respectively. The desired neural network configuration setup is shown in Figure 5.5 and consists of

***Input layer*:** Each of 2D C-scan image matrix of size (50 X 50) is transformed to column vector (50 X 50, 1). In this way column vector of all 81 samples are stacked to form a 2D input matrix (50 X 50, 81). This input matrix is fed to input layer of neural network for training. This has enabled the proposed neural network to estimate size and shape of target from 2D C-scan image for the considered target shape.

***Hidden layer*:** The middle layer consists of 80 neurons. The numbers of neurons are chosen on the basis of trial and error in order to maintain the balance between ANN system complexity as well as minimizing the output error.

***Output layer*:** In order to estimate shape and size of target, output teaching matrix was assigned as a binary matrix according to shape and size of target considered. For example in the case of rectangle shape of size (50cm X 30cm) is assigned binary image to its corresponding rectangular target and rectangle shape of size (50cm X 30cm) is assigned binary image to corresponding rectangular target. Now rectangular shape target has been oriented to various angles and for each orientation binary matrix of same size corresponding to rectangular target size has been assigned because aim is to estimate the shape. In this way binary image assigned will be same for any orientation of the same size.

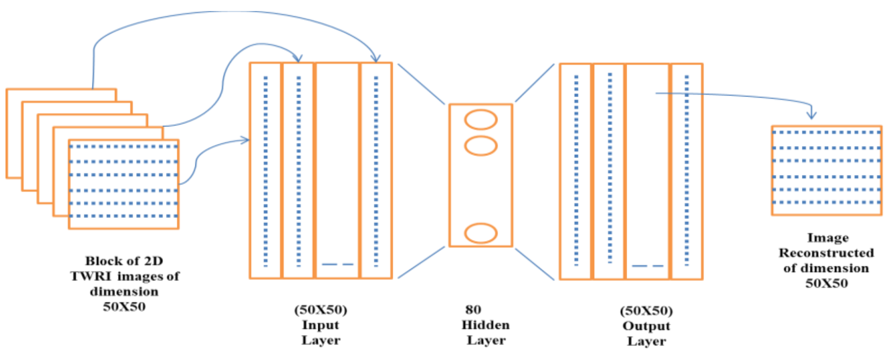


Figure 5.5. Configuration of neural network for target recognition.

Sigmoid transfer function is chosen for the hidden and output layer so that output of a neural network lies between 0 and 1 which is required for image reconstruction. Mean squared error (MSE) criterion is used as learning algorithm to train the neural network which is defined as

$$mse = \frac{1}{N}\sum_{i=1}^{N} e_i^2 = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{r}_i - a_i)^2 \tag{5.5}$$

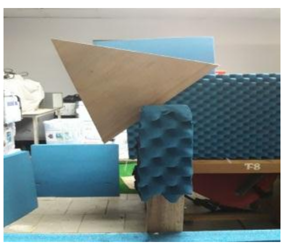
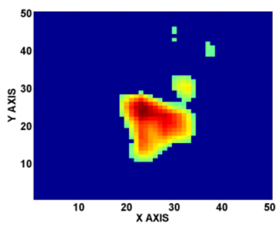
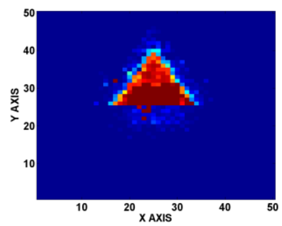
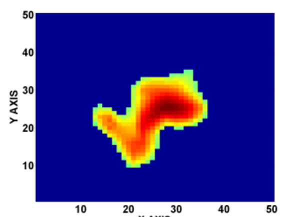
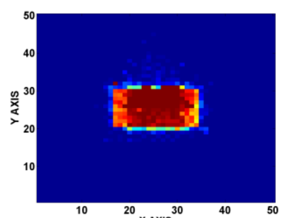
where 'a' is the network output and 'r' is the target output. In MSE criteria the neural network first produces its own output vector 'a' according to fed input vector and then compares the output vector with the desired target vector 't'. If error occurs, then the weights are adjusted using scaled conjugate gradient method to reduce the difference till

MSE reaches below 0.01 for optimum performance. The performance of neural network is better for lower value of mean square error.

5.3 Results and Discussion

Table 5.4 shows results of image reconstructed using trained neural network for few of data samples used for training, i. e., WTR3, and MRR3 (notations as per Table 5.3). Actual photographs of the corresponding targets are also shown for reference.

Table 5.4. Results of image reconstructed for training data samples.

Actual target photograph	**Thresholded 2D image**	**Reconstructed image using ANN**	**MSE**
(1) Target Id – WTR2 			0.0065
(2)Target ID-MRR3 			0.0168

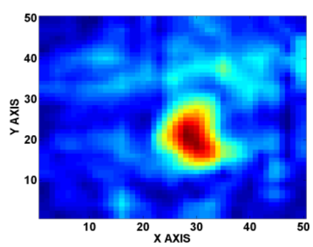
Neural network is trained using corresponding binary matrices for example, target id WTR3, which is wooden triangular shape having size 35 cm X 35 cm at 135˚ orientation, is assigned same size and shape binary image and target id MRR3, which is metallic rectangular shape having size 50 cm X 30 cm at 135˚ orientation, respectively, are assigned corresponding binary image. It can be inferred that the trained neural network successfully reconstructs exact shape and size of target for corresponding different shape and size of target at any orientation, with appreciably low mean square error values, viz., 0.0065, 0.0168, respectively.

5.3.1 Validation of Developed ANN Model for the Scale and Rotation Invariant

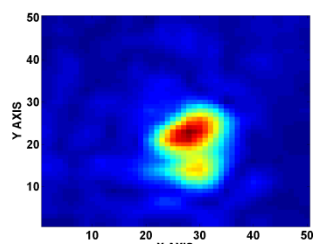
It is one of the most critical tasks to find the size and shape of targets behind wall in case of different size and rotation. Different shapes of the targets behind wall are scanned and corresponding sizes are generated by morphological technique. For example, the shape of target id MSR1, which is Metal Square having size 30 cm X 30 cm at 0˚ orientation, is really scanned and image got generated using delay and sum imaging algorithm. The image of target id MSV4, which is metal square having size 35 cm X 35 cm at 0˚ orientation, is generated by morphological technique. It thus saves large scanning time. To generate the actual shape of targets, the ANN technique is used. The thresholded delay and sum beamformed image is used to train the neural network with the help of corresponding binary image, for example, target id WTR1, which is wood triangular shape having size 35 cm X 35 cm at 0˚ orientation, is assigned same size and shape binary image and target id WTV4 and WTV5, which is wood triangular shape having size 40 cm X 40 cm at 0˚ and 45˚ orientation, respectively, are assigned corresponding binary image. After training, the performance of a trained artificial neural network needs to be verified through independent data to confirm its usefulness and practicality. Therefore, after training the neural network, the accuracy for scale and rotation invariant is verified by 13 independent target samples that are not used for train the network. Figures 5.6(a-l) show the 2D C-scan through-the-wall radar image of the independent test samples of a wood triangular target of size 35 cm X 35 cm X 35 cm at 45˚ orientation, metal triangular target of size 35 cm X 35 cm X 35 cm at 45˚ orientation, metal square target of size 30 cm X 30 cm at 45˚ orientation, wood triangular target of size 50 cm X 50 cm X 50 cm at 0^0 orientation, wood triangular target of size 50 cm X 50 cm X 50 cm at 45 orientation, wood square target of size 35 cm X 35 cm at 0^0 orientation, wood square target of size 35 cm X 35 cm at 45^0 orientation, wood rectangular target of size 55 cm X 35cm at 0^0 orientation, wood rectangular target of size 55 cm X 35cm at 135^0 orientation, metal square target of size 35 cm X 35 cm at 0^0 orientation, metal square target of size 35 cm X 35 cm at 45^0 orientation, and metal rectangular target of size 55 cm X 35cm at 135^0 orientation.

Table 5.5. List of independent target samples used for validation of artificial neural network.

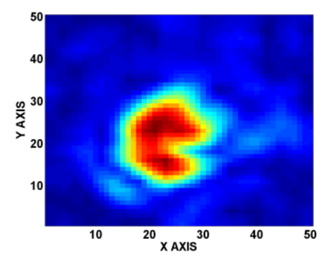
S. No.	Shape	Target I/D	Size	Orientation	Material	Generated Image
1.	Triangle	WTR16	50cmX50cmX50cm	0	Wood	Real
2.	Triangle	WTR17	50cmX50cmX50cm	45	Wood	Real
3.	Square	WSR16	35cmX35cm	0	Wood	Real
4.	Square	WSR17	35cmX35cm	45	Wood	Real
5.	Square	MSR16	35cmX35cm	0	Metal	Real
6.	Square	MSR17	35cmX35cm	45	Metal	Real
7.	Rectangle	WRR16	55cmX35cm	0	Wood	Real
8.	Rectangle	WRR17	55cmX35cm	135	Wood	Real
9.	Rectangle	MRR16	55cmX35cm	45	Metal	Real



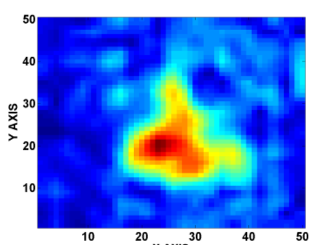
(a) Target ID: WTR2



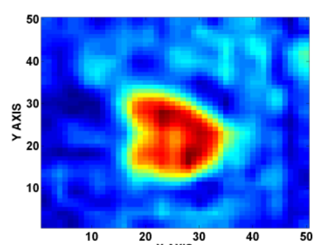
(b) Target ID: MTR2



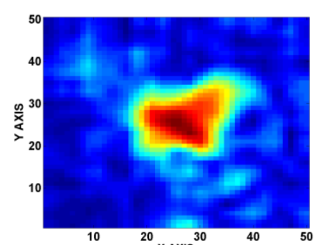
(c) Target ID: MSR2



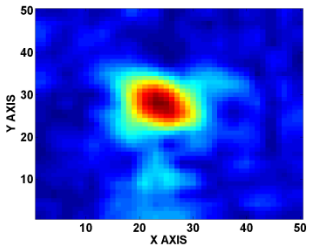
(d) Target ID: WTR16



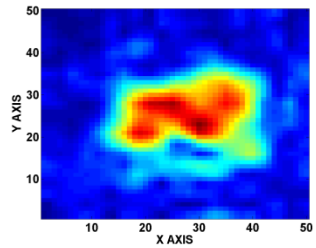
(e) Target ID: WTR17



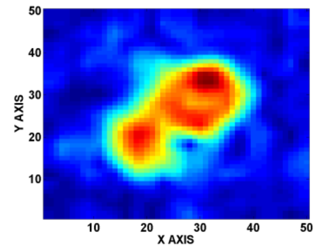
(f) Target ID: WSR16



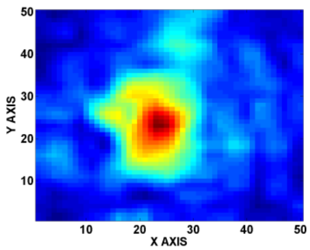
(g) Target ID: WSR17



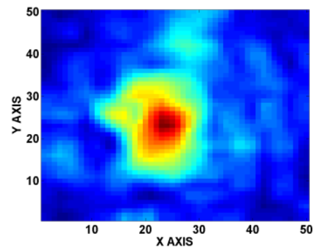
(h) Target ID: WRR16



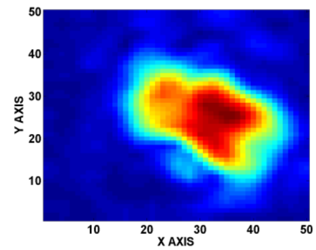
(i) Target ID: WRR17



(j) Target ID: MSR16



(k) Target ID: MSR17

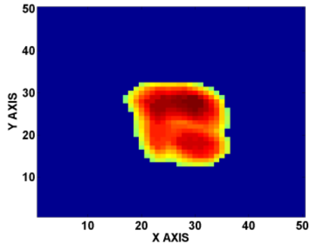
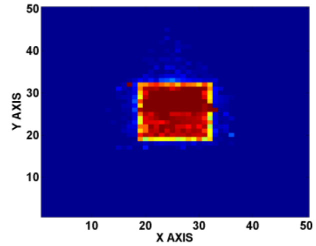
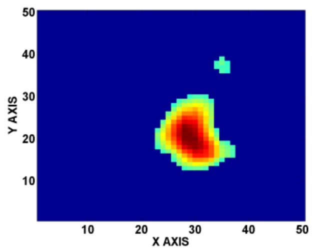
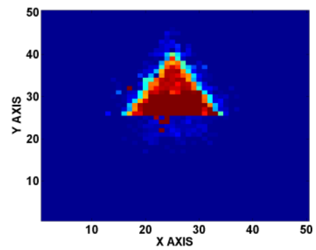
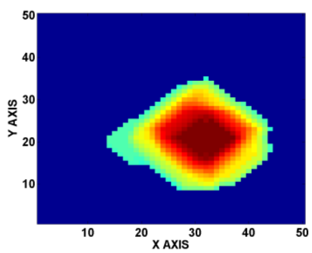
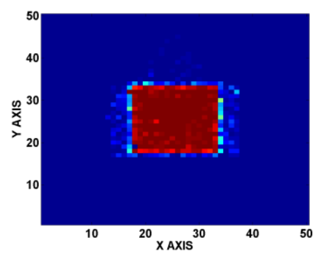
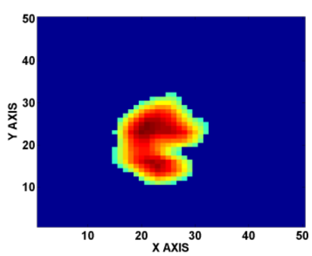
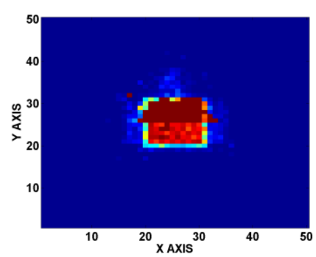


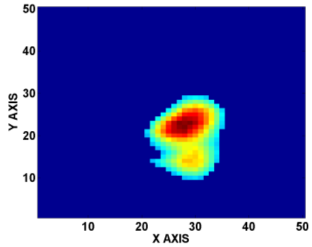
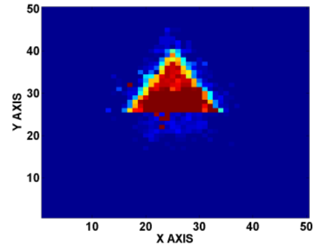
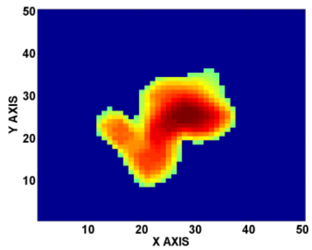
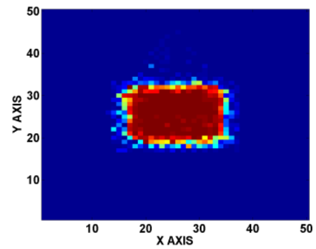
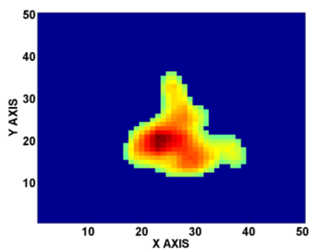
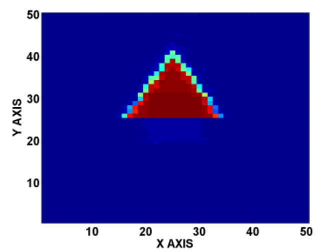
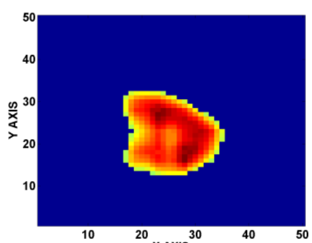
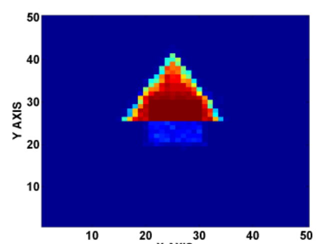
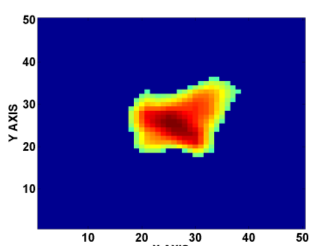
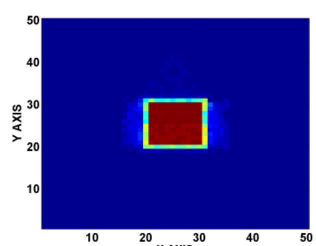
(h) Target ID: MRR16

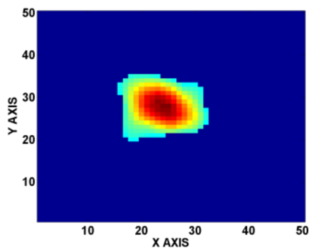
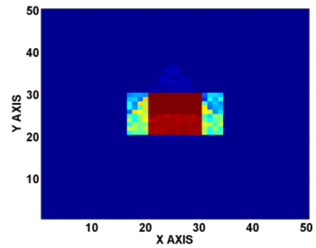
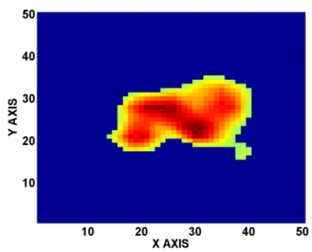
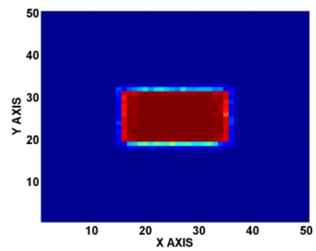
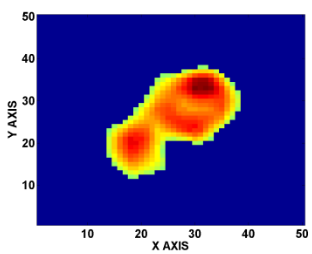
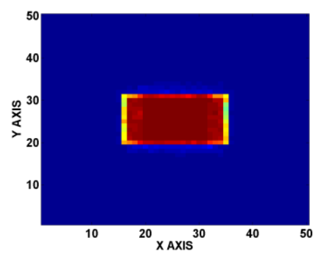
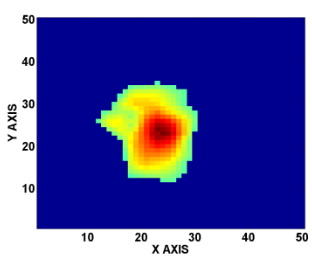
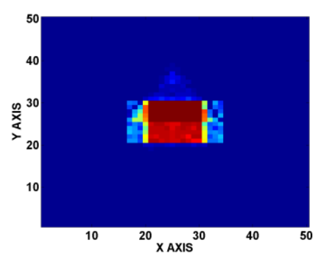
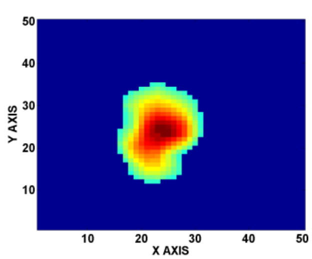
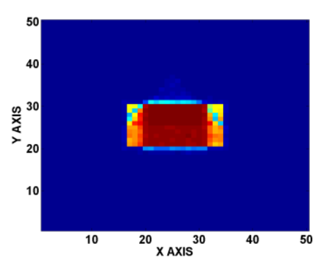
Figure 5.6. 2D C-scan through-the wall radar image of targets id **(a)** WTR2, **(b)** MTR2, **(c)** MSR2, **(d)** WTR16, **(e)** WTR17, **(f)** WSR16, **(g)** WSR17, **(h)** WRR16, **(i)** WRR17, **(j)** MSR16, **(k)** MSR17 and **(h)** MRR16.

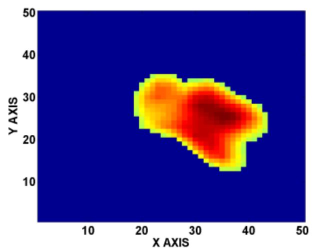
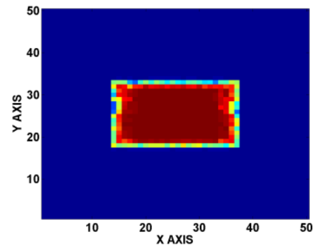
These independent samples are thresholded using statistics based thresholding, as discussed in Chapter 4, and fed to the trained neural network. A corresponding binary image is obtained as shown in Table 5.6. The mean square error (MSE) between ANN output image and desired image is also shown. As shown in Table 5.6, WTR2, MTR2 MSR2, WTR16, WTR17, WSR16, WSR17, WRR16, WRR17, MSR16, MSR17, and MRR16 (notations as per Table 5.3 and 5.5) target images are recognized as a output images having true size and shape, with MSE of 0.0078, 0.0023, 0.0063, 0.0487, 0.0494, 0.0053, 0.0155, 0.0021, 0.0019, 0.0111, 0.0166, 0.0391 respectively, which shows the capability of proposed rotation and scale invariant neural network for shape and size estimation of target for the considered regular target shapes. Thus the proposed neural network with these test samples shows good performance.

Table 5.6. Result of the image reconstructed for an independent test data samples.

Test target (Thresholded Image)	**Output reconstructed image**	**MSE**
 Target ID-WSV7		0.0135
 Target ID-WTR2		0.0071
 Target ID- WSV15		0.0208
 Target ID: MSR2		0.0122

 Target ID: MTR2		0.0072
 Target ID: MRV6		0.0215
 Target ID: WTR16		0.0487
 Target ID: WTR17		0.0494
 Target ID: WSR16		0.0053

 Target ID: WSR17		0.0155
 Target ID: WRR16		0.0021
 Target ID: WRR17		0.0019
 Target ID: MSR16		0.0111
 Target ID: MSR17		0.0166

 Target ID: MRR16		0.0311

5.4 Conclusion

In this chapter, a novel application of artificial neural network for recognition of shape and size of target behind a wall using through-the-wall radar has been presented. For this purpose, an active microwave SFCW radar imaging system has been designed to capture the C-scan data of regular triangular, square and wooden shape targets behind a wall. From these data, through the wall images are generated using delay and sum beamforming algorithm. These images have been segmented using statistics based thresholding method and further used for training of artificial neural network for development of target recognition model. To develop scale invariant ANN model, large numbers of thresholded through-the-wall radar images for training are required. The number of through-the-wall radar can be increased with the help of multiple scanning of various targets behind the wall but it requires long time. Therefore, to save the time, the through-the-wall radar has been increased with the help of morphology technique. The performance of various signal processing steps for target recognition has been validated taking resort with the experimental results. The proposed neural network based signal processing technique ones trained with sample images has showed good performance with the test images and has recognised nearly actual shape and size of target.